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FORECASTING WORKLOAD FOR DEFENSE LOGISTICS AGENCY DISTRIBUTION

December 2014

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FORECASTING WORKLOAD FOR DEFENSE LOGISTICS AGENCY DISTRIBUTION

ABSTRACT

The Defense Logistics Agency (DLA) predicts issue and receipt workload for its distribution agency in order to maintain adequate staffing levels and set proper rates for customers. Inaccurate forecasts lead to inaccurate staffing, subsequently leading to inaccurate pricing. DLA's current regression forecasting model is no longer adequate for predicting future workload for DLA Distribution. We explore multiple forecasting techniques and provide a methodology for selecting a model that is a viable and accurate alternative for DLA. Our methodology encompasses "best-fit" determination, a comparison of predictability through back-casting, and a sensitivity exercise to see reaction and stability of our selected models' predictions. Finally, we compare our best performing model with the current regression model to see what would have been reported if our model had been used instead of the current model for recent Program Budget Review (PBR) cycles. Our results suggest that an auto-regressive integrated moving average (ARIMA) model used with critical assessment and managerial judgment offers a viable alternative to the current model for predicting distribution workload.

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	autocorrelation
ARIMA	auto-regressive integrated moving average
AVN	Aviation
BSM	Business Systems Modernization
CIT	consumable items transfer
C&E	Construction and Equipment
C&T	Clothing and Textiles
CD	customer direct
DC	distribution center
DD	Defense Logistics Agency Direct
DES	double exponential smoothing
DLA	Defense Logistics Agency
DOD	Department of Defense
DORRA	DLA Operations Research and Resource Analysis
DSA	Defense Supply Agency
DWCF	Defense Working Capital Fund
EBS	enterprise business systems
ERP	enterprise resource planning
ES	exponential smoothing
FTE	Full Time Equivalent (Employee)
FY	fiscal year
Ind HW/IH	Industrial Hardware
I&R	issues and receipts
LI/PE	lines (issue or receipt) per paid equivalent
MA	moving average
MAD	mean absolute deviation
MAPE	mean absolute percentage error
NLC	net landed cost
O&M	Operation and Maintenance
OCO	overseas contingency operations
OPTEMPO	operational tempo

PAC   partial autocorrelation
PBR   Program Budget Review
PE   percentage error

SES   simple exponential smoothing

WL   workload

I. INTRODUCTION

A. PURPOSE

The Defense Logistics Agency (DLA) manages the distribution (receipt, storage and issue) of material across all components of the Department of Defense (DOD). We researched forecasting models to more accurately predict DLA's distribution workload. This distribution workload forecast is used to help properly staff distribution centers and set rates to fully recover costs. So, workload forecast accuracy is important for DLA to remain cost-competitive.

B. THE PROBLEM

DLA's current forecasting method is not sufficiently accurate in predicting workload, and this degrades their ability to set rates, staff distribution centers and fully recover costs. Inaccurate workload predictions can contribute to improper staffing decisions at the distribution centers (DC), affecting order processing times.

According to DLA personnel, the current regression model used to estimate DLA distribution processing workload has become an unreliable tool. The model's ineffectiveness was accentuated by the recent budget downturn across the Department of Defense.

C. RESEARCH QUESTIONS

Our research examined the current regression model DLA uses to forecast its workload across its distribution centers. We identified factors and issues affecting the accuracy in predicting DLA distribution workload. Our research sought to answer two primary questions. First, what are the shortcomings of the current regression model? Second, are better forecasting methods or tools available to provide more accurate forecasts?

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II. BACKGROUND

A. DEFENSE LOGISTICS AGENCY

The DLA, originally established as the Defense Supply Agency (DSA) in 1961, is critical to providing material and service support to our military services and our national security objectives.

1. History

Prior to DSA's establishment, each military service managed its own consumable and commodity items as well as supply processes. The goal of a single, consolidated management agency was to create efficiencies in procedures and reduce inventories and overhead, while providing timely support for the military services and contingency operations (Defense Logistics Agency [DLA]*, 2011).*

Under the direction of Secretary of Defense Robert McNamara, DSA consolidated the following eight single management agencies (DLA, 2011):

- Defense Clothing and Textile Supply Center (Philadelphia)

- Defense Construction Supply Center (Columbus)

- Defense General Supply Center (Richmond)

- Defense Medical Supply Center (Brooklyn)

- Defense Petroleum Supply Center (Washington, DC)

- Defense Subsistence Supply Center (Chicago)

- Defense Traffic Management Services (Washington, DC)

- Defense Logistics Services Center (Washington, DC)

The administration of these eight commodity centers began the expansion and increased responsibilities that DSA (renamed DLA in 1977) experienced over the next several decades.

In 1990, the Department of Defense directed DLA to manage the unified material system, consolidating all the distribution depots in an effort to reduce overhead and inventories. To achieve this, DLA began adopting commercial business practices, automating and modernizing their depots and processes. DLA introduced an enterprise resource planning (ERP) initiative called the Business Systems Modernization (BSM) program, which it integrated throughout its supply centers by 2007 (DLA, 2011).

According to DLA *Loglines* (2011), in the 1990s, DLA reduced the number of organizations reporting to the DLA director from 42 to six through integrating business units. This integration continued through 2010 as business units fell under the DLA unified integrated enterprise. Base Realignment and Closure initiatives throughout the 2000s pushed this further, with the goal of making DLA more efficient.

In the wartime years following 9/11, DLA's business doubled. DLA focused on customer support, getting the right material at the right time to the right place to sustain combat operations. The environment required DLA to engage the services in demand planning and streamline their efficiency and accuracy in building business practices (DLA, 2011).

2.   DLA Operations

DLA provides a full spectrum of logistics, acquisitions, and technical services to the Army, Navy, Air Force, Marine Corps, and other federal agencies. DLA provides nearly all consumable items to America's military forces and 85% of the military's spare parts (DLA, 2014). The consumables DLA provides are food, fuel and energy, clothing, medical supplies, and construction equipment (DLA, 2014). Over time, DLA has also increased its humanitarian missions and is one of the first responders when a crisis occurs (DLA, 2011).

DLA is headquartered in Fort Belvoir, but it also operates in 48 states and 28 countries to support the warfighter. It employs 25,500 civilian and military employees and ranks within the top 15th percentile of Fortune 500 companies, taking into account $39 billion in sales and revenue and the value of the services they provide (DLA, 2014).

Although DLA has several other operations, below are the key responsibilities relevant to this study (DLA, 2014):

- Manages nine supply chains and nearly 6 million items

- Manages 25 distribution centers worldwide

- Supports roughly 2,400 weapon systems

- Administers the storage and disposal of strategic and critical materials

- Processes on average 98,475 requisitions and over 9,000 contract actions a day

A critical activity in the DLA enterprise that this study directly pertains to is DLA Distribution.

3. **Distribution**

According to DLA's 2012 *Annual Financial Report*, DLA Distribution falls under the organization's supply management business area. Supply management processes make up 99% of assets, liabilities, revenues, and costs on the financial statement (DLA, 2013).

DLA Distribution is a field activity for the agency and was established in October 1997. Its headquarters is in New Cumberland, Pennsylvania (DLA, 2013). In addition, DLA operates 25 distribution centers in 12 states and seven countries (DLA, n.d.-c.). DLA Distribution's mission is to leverage global distribution networks to enable logistics solutions (DLA, n.d.-b). The Distribution vision is to be the preferred source of global distribution support for the military services and government agencies (DLA, n.d.-b).

DLA Distribution's primary functions consist of receiving, storing, and issuing material. Processes included in these functions are off-loading cargo, processing and routing, inspection, classification, warehousing, packaging and transportation planning (DLA, n.d.-c). DLA Distribution refers to these processes as workload. For this study, workload is only measured in issues and receipts as defined below (DOD, 2014):

Receipt: The processes and the work required to receive an item from a customer or supplier by a DLA distribution center to include off-loading, processing/routing, inspection, classification, and stocking. Receipts are measured in line items.

Issue: The processes and the work required to issue an item to a customer by a DLA distribution center to include processing/routing, inspection, packaging, and transportation planning. Issues are measured in line items.

B.   OVERVIEW OF FORECASTING

Forecasting is a critical element for business operations and planning. Supply chain enterprises use forecasts to estimate inventory levels, work schedules and, in the case of DLA, to estimate workload and subsequent staffing levels as well as set prices for customers. According to an Oracle Corporation white paper that discusses forecasting, however, "The main principle of forecasting is to find the model that will produce the best forecasts, not the best fit to the historical data. The model that explains the historical data best may not be the best predictive model" (Oracle Corporation, 2006, p. 1).

1.   Elements of Forecasting

The four broad elements of forecasting described below serve as a framework for working with forecast models. Strategic and tactical forecasting are tied to time. Quantitative and qualitative forecasting are associated with managerial decision making based on forecasting.

a.   *Strategic and Tactical Forecasting*

There are two main types of forecasting: strategic and tactical (Jacobs & Chase, 2011). Strategic forecasting is a medium- to long-term outlook that is used to help set the strategy of how to meet an aggregated workload (Jacobs & Chase, 2011). Tactical forecasting is a short-term outlook used to make day-to-day decisions of how to meet short-term workload (Jacobs & Chase, 2011). In the case of DLA, tactical forecasting may be used at individual distribution centers as they attempt to manage daily workload fluctuations and process time requirements. Strategic forecasting is used to set prices for

the services as well as plan out medium- to long-term (at least six months) staffing requirements.

For the purposes of this study, Jacobs and Chase's timeframe definitions (2011) are used since they are terms typically used in business forecasting. Short term is defined as less than three months. Medium term is defined as three months to two years. Long-term forecasting is defined as greater than two years. DLA is attempting to forecast medium- to long-term workload using aggregated sales (the dollar value of items sold by DLA to customers directly, known as DLA Direct Sales). Workload is related to these sales but is measured in the number of transactions that occur in the form of issues and receipts. Some form of work is required to process these. The workload forecast is what helps manage staffing requirements and helps DLA set prices for the services because it must account for the costs of those workers in the price.

Other variables, however, may also influence workload. Seasonal or cyclical changes to customer orders may increase or decrease the amount of issues and receipts distribution centers take on. A decreasing budget for a service may not necessarily mean a decrease in issue and receipt lines. Perhaps, the service is buying items in smaller increments, which actually increases the number of receipts and issues. Consumable items that are purchased regardless of budget, cycle, or season may lend themselves to historical data being similar to forecasted data.

b.   *Quantitative and Qualitative Forecasting*

Additionally, policy changes and management decisions may also affect workload. These additional variables require qualitative (judgment) input to the forecasting methodology.

Managerial adjustments are usually made based on information that is not available to the statistical model. Intuition, expert opinion, and experience may facilitate a fairly accurate forecast. In a 1994 survey of forecasters at U.S. corporations, 91% either always made adjustments or sometimes made adjustments to their mathematical forecast results (Syntetos, Boylan, & Disney, 2009). The inevitable errors in mathematical models can be ameliorated by decisions managers make. The model's job is to get as close to

100% accurate as possible using data available. The manager's job is to make decisions on how to influence the remaining error.

Although qualitative techniques are used to fine-tune forecasts, quantitative techniques are used for the bulk of forecasting because they use hard data that stem from business operations. At the same time, these quantitative methods need not be complicated. A study by Makridakis (1982) highlights that simple forecasts perform as well as if not better than complicated ones. "It is not necessarily the case that complex methods produce more accurate forecasts than simple methods…the more noise or randomness in the data, the less important it is to use sophisticated methods" (Orchowsky, Kirchoff, Rider, & Kem, 1986, p. 7). An example of a simple technique is exponential smoothing. A 2006 summary by Gardner of all studies done since 1985 (65 total) that included exponential smoothing resulted in 90% of them reporting that smoothing methods offered more accurate forecasts (Syntetos et al., 2009).

The acknowledgement that simple forecasts are just as good as complicated ones is important for choosing the right forecast model for businesses. First, they are easy to use and do not take a lot of time; the data that are likely inputs to the model are readily available (e.g., sales, demand, lines). Second, they do not require a specially qualified person or cost a lot to run the models. We can break down common models that are still used prevalently in the supply chain industry into two main types: time-series models and causal models.

2. Forecasting Techniques

The following is a basic overview of common forecasting techniques.

a. *Time-Series Models*

Several time-series models are prevalent in business planning. The three that we will look at for this study are moving average (MA), exponential smoothing (ES), and auto-regressive integrated moving average (ARIMA).

(1) Moving Average

The moving average technique uses the mean of a designated number of periods to forecast the next period. The equation that we use is the following (Jacobs & Chase, 2011):

$$F_t = (A_{t-1} + A_{t-2} + A_{t-3} + \ldots A_{t-n})/n$$

where

F_t = the forecasted value
A_{t-1} = actual value in the previous period
A_{t-n} = actual value in the nth period
n = number of periods

The moving average technique is very simple to use. That simplicity may not allow it to accurately forecast seasonal data or trends, however (Orchowsky et al., 1986). A weighted moving average can also be used to indicate the importance of a previous period to the forecasted value. The equation used is the following (Jacobs & Chase, 2011):

$$F_t = w_1 A_{t-1} + w_2 A_{t-2} + w_3 A_{t-3} + \ldots w_n A_{t-n}$$

where

w = weight of actual value in previous period

(2)   Exponential Smoothing

Exponential smoothing is still the most common forecasting technique. It uses a constant value, called a smoothing constant (α), that represents the rate of reaction to a difference between forecasted demand and actual demand for a time period. The premise of exponential smoothing is that the most recent data is more influential than older data (Jacobs & Chase, 2011). The equation for simple exponential smoothing (SES) used is the following (Jacobs & Chase, 2011):

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where the new forecast is equal to the previous period's forecast plus a portion of the error. Advantages of SES are that it is fairly accurate (evidenced by its popularity) and

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easy to use. It still will lag behind any trends present, however, and cannot forecast season data (Orchowsky et al., 1986).

Double exponential smoothing (DES) uses two equations with two smoothing constants to account for trend. The equations used are the following (Orchowsky et al., 1986):

$$S'_t = \alpha x_t + (1-\alpha)S'_{t-1}$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1}$$

$$a_t = 2S'_t - S''_t$$

$$b_t = (\alpha/1-\alpha)(S'_t - S''_t)$$

$$F_{t+m} = a_t + b_t m$$

where

S'_t = the single smoothed value for the current time period

S''_t = the double smoothed value for the current time period

X_t = the actual value for the current time period

a_t = the estimated level at the current time period

b_t = the estimate of the trend at the current time period

m = the number of periods ahead to be forecast

F_{t+m} = the forecast value for "m" periods ahead

(3)   Auto-Regressive Integrated Moving Average

Although an auto-regressive integrated moving average (ARIMA) model is a more complicated forecasting method, it accounts for several parameters together, including ES and MA, as well as decomposition of trends and seasonality. Since the data used in this study is non-stationary (exhibits a trend) and has seasonal characteristics, an ARIMA model is appropriate to analyze.

The ARIMA model used for this study is the following (Hoff, 1983):

ARIMA (p,d,q) x (P,D,Q) s

where

p = the number of auto-regressive (AR) parameters

d = the number of differencing used to make the data stationary

q = the number of MA parameters

P = the number of seasonal AR parameters

D = the number of differencing to make seasonal patterns stationary

Q = the number of seasonal MA parameters

s = the number of periods per season

*(a)   Autocorrelations (*AC*) and Partial Autocorrelations (*PAC*)*

In order to determine what AR, MA, or ARMA parameters will work best, the data series' autocorrelations (AC) are determined, indicating how a data series is related to itself over time (Hoff, 1983). Analyzing theoretical patterns of ACs and PACs can help in determining the number of AR and MA parameters, both non-seasonal and seasonal, but actual data series will likely not adhere to these exact patterns, so comparing with different parameters will narrow down the best models. Software programs, such as JMP used in this study, can calculate ACs and PACs as well as the confidence intervals to determine whether the ACs are significant.

(b)   Model Verification

Too many parameters can make an ARIMA model overly complicated with no value added to the model. As with other techniques, verification of an ARIMA model is needed to ensure an adequate yet not overly complicated model. The ACs of residuals can be analyzed to determine whether too many or too few AR and MA parameters are used. The coefficient of determination, R^2, can also be used, measuring how much the model accounts for variation in the data series (Hoff, 1983). The R^2 value is a quick metric to compare models; the perfect fit for a time series data set, however, may not be good at predicting future values. It may only be good at fitting the original data series;

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therefore, a high R^2 value should be combined with other validation techniques, which are discussed in the Forecasting Errors section.

The ARIMA model seems complicated but, with the assistance of statistical software, the complexity may lead to a superior forecast, especially with trending, seasonal data that is related to various prior time periods. A critical element to using ARIMA modeling is to create a model that forecasts just as well as it models the original data. Too many parameters leads to a perfect fit of the original time series but are a poor predictor of future values.

b. *Causal Models/Regression*

Causal regression models use independent variables other than time to predict dependent variables. For example, in the case of DLA's current workload forecast model, they use sales data as an independent variable, or indicator, that causes a change in the dependent variable, workload. The equation used for linear regression is the following (Jacobs & Chase, 2011):

$$y = B_0 + B_1x$$

where

y = the dependent variable being forecasted

B_0 = the y-intercept

B_1 = the slope

x = the independent variable

The advantage of regression analysis is that it takes into account other factors that may influence the value being forecasted, and which do not rely on trends over time. This may be a reason why the current DLA workload model is causal-based. It is also easy to calculate using Microsoft Excel. The disadvantage of causal regression is that the independent variable(s) needs to be identified and be a leading indicator(s) of the value being forecasted. Many times, these other factors are forecasted themselves, meaning the variable being forecasted is dependent on another forecasted value.

3. Forecasting Error

Another key element of forecasting is recognizing error. No forecasting method is 100% accurate. Therefore, the forecasting error is the difference between what was forecasted and what actually happened (Jacobs & Chase, 2011). In this study, we look at R^2 (as discussed in the previous section) to determine how well a model fits the actual data, mean absolute deviation (MAD), and mean absolute percentage error (MAPE).

MAD measures how far values are from an expected value. It is the average error in absolute terms (Jacobs & Chase, 2011). The equation used to calculate MAD is the following (Jacobs & Chase, 2011):

$$MAD = (\sum |A_t - F_t|)/n$$

t = time period number

A_t = actual value for the period t

F_t = forecast value for period t

n = total number of periods

MAPE relates the error back to the average value, which is useful in determining what percent error to expect (Jacobs & Chase, 2011). The following equation is used to calculate MAPE (Jacobs & Chase, 2011):

$$MAPE = MAD/Average\ Value$$

C.   DLA FORECASTING

By the nature of its business, DLA was using simple forecasting techniques, along with industry, over fifty years ago. It began critiquing its forecasting in 1963. This original study recommended ES over a MA technique (Orchowsky et al., 1986). Several years later, another study was done showing that DES was more accurate (Orchowsky et al., 1986). Over the next 20–30 years, studies identified ES with a smoothing constant (α) of .2 to offer the best demand forecast, which resulted in DLA using a modified and slightly incorrect version of the DES model described in the previous section (Orchowsky et al., 1986).

Forecasting efforts were also conducted within the military services that, until the past two decades, accounted for repairable and consumable items. This led the services to use program factors in their forecasting. In 1983, Boeing conducted a study that compared forecasting techniques for Army and Navy data. The study resulted in an eight-quarter MA technique to perform best out of the simple methods. An ARIMA model also performed well, but ES and regression did not perform well (Orchowsky et al., 1986).

This led to a study done in 1989 that looked at forecasting contracting workload at DLA. A causative model using service activity consisting of equipment usage (e.g., flying hours), personnel, and budgetary activities (procurement and O&M dollars) was tested. It did not perform adequately enough to change the current methods they were using (Schwarz & Brooks, 1989). Another study in 1991 analyzed the impact of decreasing DOD budgets and consumable item transfers (CIT) (the process was just starting to transfer these items from the services to DLA control) on DLA "demand workload" (Baker, 1991). The recommendation was to use the procurement budget as a leading indicator as well as CIT in regression analysis to forecast demand in dollars (Baker, 1991).

By 1996, consolidation was not complete yet, so the services were still predicting workload consisting of issues and receipts that were predicted to be at DLA distribution depots. DLA had no formal model to estimate this workload. They would predict based off one or two quarters and expand that for the entire year. It assumed the percent change from previous year to current year workload could be applied to future years. It then took the services' forecasts and averaged it with theirs to get the forecast for the year (Warbrick, 1996). Several things made this forecasting method inadequate. It was based on service data that was also forecasted with assumptions of its own, one of which was the assumption that the percent change in sales was equivalent to the percent change in total requisitions (issues and receipts). Judgmental forecasting was also heavily used by the services (Warbrick, 1996). Warbrick concluded in his thesis that causal-based factors, in particular, operations and maintenance (O&M) budget and a measure of operational tempo (OPTEMPO) could predict workload for Navy workload at DLA distribution

depots (Warbrick, 1996). This recommendation influenced the linear regression technique used in this study.

1. DLA's Current Workload Forecasting Model

The following is our understanding of the current model used by DLA to predict distribution workload.

a. Introduction

The current model is a causal model using DLA Direct Sales (DD Sales) as the independent variable and issues and receipts as the dependent variable in a linear regression analysis. DD Sales result from items that are stored at a distribution facility and require DLA direct labor to either issue to a customer or receive from a supplier to replenish stock. The workload defined is the total number of issues and receipts that require personnel and the subsequent labor to support. DD Sales differ from customer direct (CD) Sales, which do not require direct labor during the transactions. The current state of this model is under evaluation as DOD and DLA environmental factors, such as contracted or commercial logistics support, may be affecting DLA Distribution workload. The current model may no longer meet DLA's challenging environmental needs since qualitative techniques are used to adjust forecasted results that are believed to be inaccurate.

Some possible reasons why the current model is inaccurate are the following:

- Sales are not a good leading indicator of lines received or issued. For example, if service budgets are decreasing, it is possible that services are ordering smaller quantities more frequently, which would actually offer no change or an increase to the issue and receipt workload involved.

- Sales are being estimated themselves, leading to compounding of forecast errors (Lee, Padmanabhan & Whang, 1997). Sales are taken from the services and different supply chains based on any number of factors that the services deem will influence their purchase figures.

- The decrease in DOD budgets is having a significant effect on DLA's ability to forecast workload.

- The model aggregates sales, issues and receipts. Maybe one model is not the best fit for all the supply chain sales. Forecast error may be driven by structural change in one supply chain, while the others remain more predictable.

- Other external factors may influence the workload data that are not correlated with sales. There may be a seasonality characteristic or a relationship with other external indicators.

DLA's causal-based regression model attempts to predict the annual distribution workload measured in terms of issues and receipts from sales. The workload forecast projections for each fiscal year (FY) are based on the previous twelve months of actual DLA Direct (DD) sales, processing and storage workload (DOD, 2014, pp. 81–82). Each supply chain provides sales estimates and percentage of DD sales stored at distribution centers. Only the sales from four supply chains are used to determine workload across DLA: Maritime, Aviation, Land, and Industrial Hardware. The other supply chains are reasoned to be inconsequential to predicting workload. The estimates of the four primary supply chains are totaled to provide yearly sales projections. The sales estimates are applied to the regression analysis, predicting future fiscal year estimates for total number of lines. DLA uses the forecasted workload values to make decisions on staffing requirements, distribution center spending plans, and proper rate setting to recover costs.

b.   *Current Model Assumptions*

The following assumptions are included in the current regression model:

1.   The correlation between sales and workload is strong enough to accurately predict workload.

2.   The estimated sales projections provided by each supply chain are sufficiently accurate.

3.   Maritime, Aviation, Land, and Industrial Hardware supply chains have the only significant impact on workload, and other supply chains (Clothing & Textiles, Medical, Subsistence, and Construction & Equipment) do not have a significant impact on workload.

4.   Sales numbers are adjusted into comparable constant dollar amounts.

c.   *Causal Indicators*

The current regression analysis is dependent on the information provided by each supply chain and the four military services. The supply chains provide sales forecasts based on system-generated modeling, customer input, and strategic policy decisions. The customer inputs are provided by each service and are projected demand requirements based on operational planning estimates. The sales estimates included in the workload regression model are further segregated to the percentage of DD sales stored at distribution centers. The sales estimates are adjusted by the percentage of historic sales derived from inventory currently in storage at distribution centers. The estimates are then entered into the regression model, which generates future total FY distribution issues and receipts.

DLA charges its customers based on the issue or receipt of material from its distribution centers. The issues and receipts are converted into a *Line Charge* according to the distribution net landed cost (NLC) method for setting customer rates. The ultimate goal is to fully recover all cost associated with its distribution operations. DLA attempts to balance cost recovery with providing a fair and equitable price to each individual customer (DLA, n.d.-a). The set rate, or price to customers, directly affects the current year's sales totals. The current rate, in turn, affects the future estimated sales data, which is the causal indicator for total lines. The process is outlined in a flowchart in Figure 1.
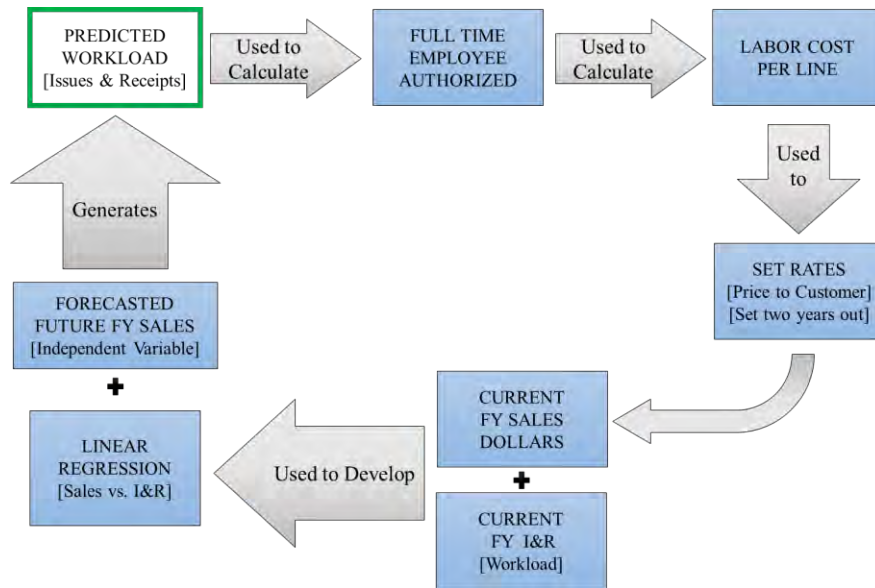
Figure 1.   The process flow in predicting DLA Distribution workload

d.   *Program Budget Review 16 Forecasting Example*

The Program Budget Review 16 (PBR16) forecasting regression analysis was conducted in March 2014. DLA used actual data from the previous 12 months, March 2013 through February 2014, to create a model predicting future workload (DLA, n.d.-d). This is shown in Table 1.

Month / FY	DLA Direct (DD) Sales @ Cost	Total Receipts & Issues
Oct - FY 14	318,324	1,078,625
Nov - FY 14	290,521	1,361,808
Dec - FY 14	281,142	744,818
Jan - FY 14	322,367	968,600
Feb - FY 14	322,495	1,028,436
Mar - FY 13	434,086	1,327,576
Apr - FY 13	241,718	1,408,681
May - FY 13	316,086	1,390,207
Jun - FY 13	336,056	1,222,920
Jul - FY 13	305,843	1,147,700
Aug - FY 13	330,255	1,329,556
Sep - FY 13	347,319	1,273,738
Total	**3,846,212**	**14,282,665**

Table 1.   DD Sales and I&R data provided in the PBR16 regression model
(from DLA, n.d.-d)

The previous twelve months of data was analyzed to produce a simple linear equation. The linear equation becomes the model to predict future distribution lines. The equation's independent variable, denoted by x, is the total monthly sales estimate for each FY. The equation's dependent variable, denoted by y, is the predicted number of total monthly distribution lines for each FY. Again, these are based on the four supply chains having the largest impact on workload. The equation produced from the PBR 16 analysis is below:

$$y = 0.618 \, x + 992081.437$$

See Figure 2 below for the graphical output of the linear regression.
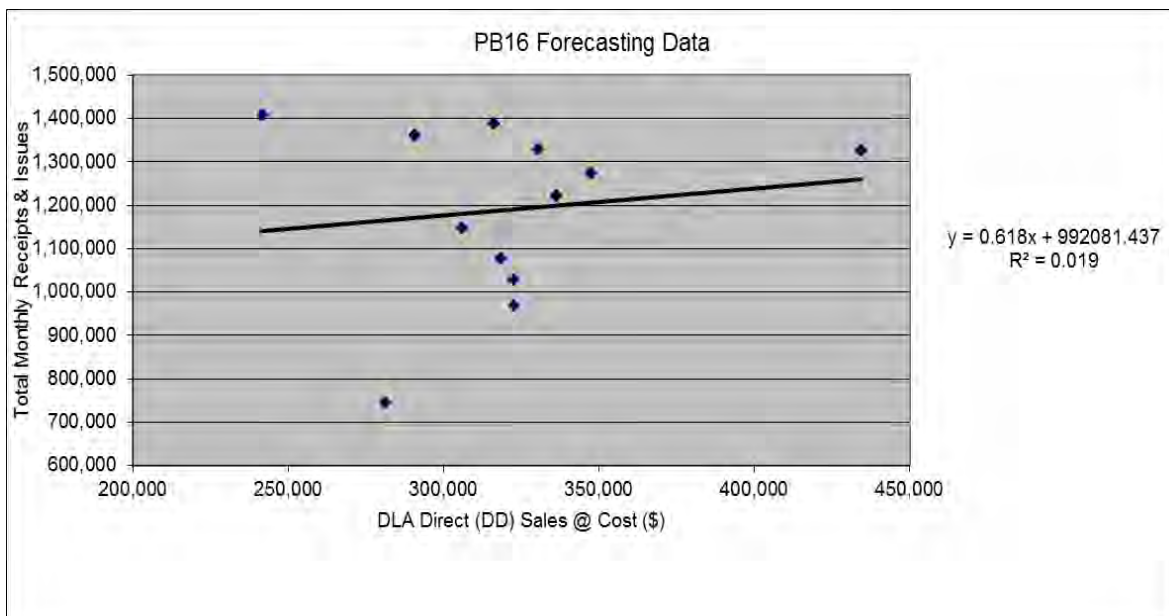
Figure 2.   Monthly DD Sales for the four primary supply chains (Avn, Land, Maritime, Ind HW) plotted to generate a linear equation used to predict future distribution workload (Monthly I&R) (from DLA, n.d.-d)

The future total FY estimated sales are entered into the equation to produce the annual estimated workload predictions. The process is conducted every year and sales are in current FY dollar amounts, FY14 for PBR 16 projections (Table 2).

Fiscal Year	Esimate DD Sales (Constant $)	Estimated Workload (Reciepts & Issues)
FY 14	3,995,428	14,374,147
FY 15	3,857,904	14,289,157
FY 16	3,746,471	14,220,291
FY 17	3,696,077	14,189,147
FY 18	3,671,969	14,174,249
FY 19	3,651,238	14,161,437
FY 20	3,624,434	14,144,872

Table 2.   PBR16 workload projections (from DLA, n.d.-d)

e.   Accuracy

The accuracy for the current model can be evaluated by looking at the R^2 to determine the model forecasting precision, the MAD and MAPE to determine the error in the models prediction. The data analysis generated an R^2 of 0.019. The R^2 is a measure of the relationship between the dependent, x variable, and independent, y variable. An R^2 close to "1" indicates a strong linear relationship between the two variables. An R^2 close to "0" indicates a weak relationship. DLA's current R^2 is almost zero. Sales, as currently measured, seem to explain almost none of the variation in workload. The MAD is 158,421 lines per month and the MAPE is 13.31% error between actual and predicted lines per month. These will be used later to compare the current model to different forecasting techniques.

2.   How the Model Is Used

DLA sets its rates and staffing levels based on the total number of lines estimated for a FY. An individual issue or receipt can be referred to as a *line*. DLA Distribution uses the predicted workload to estimate full time equivalent (FTE) employee authorizations. Staff estimates are based on a productivity goal defined as Lines (Issue or Receipt) per Paid Equivalent or LI/PE. The LI/PE is determined by using the historical average productivity achieved over past FYs. DLA Distribution takes the forecasted average monthly workload, divided by a calculated productivity goal to determine FTE employees authorized. The resulting estimated FTE staffing is included in the cost

calculation and budgeting projections for DLA Distribution as a whole. DLA Distribution's PBR forecast and rates are set two years out.

The PBR projections are further apportioned to each site based on the site's historical percentage of total overall projected workload. DLA Distribution does not allocate the actual workload to individual distribution centers. DLA HQ and individual services determine the workload allocation based on material stocks at each distribution center.

DLA Distribution HQ uses feedback provided by each distribution center to finalize site-specific workload projections in the year of execution. The workload projections are then used to calculate staffing requirements and budget allocations. The staffing targets and budget allocations are distributed to each distribution center. Individual distribution center allocations are made in the year of execution. The allocations include a spending plan (budget) and staffing authorizations (FTE). If the workload percentage allocations change from the previous year, then the adjustments to both budget and staffing will be made to match the percentage change.

D. SUMMARY

This section provided a definition, key elements, and history of forecasting in industry. By looking at historical studies summarizing forecasting techniques, we present models that are likely to provide DLA Distribution with an updated, more accurate, and easy to use forecasting technique as well as key advantages and disadvantages of each. We also described the chronology of forecasting at DLA, up until the current workload forecasting model. Lastly we described the current model and explored the possible reasons why it may not accurately predict workload, which we hope to remedy through this project.

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III. METHODOLOGY

The methodology describes our process from the recognized problem with the current DLA Distribution workload forecast model through analyzing available data to selecting a suitable forecast model and predicting DLA Distribution future workload. This process has four main tasks: 1) collection and analysis of available relevant data, 2) determination of forecasting techniques, 3) analysis and comparison of the models, 4) sensitivity and simulation analysis.

A. FOUR-STEP PROCESS

1. Collection and Analysis of Available Relevant Data

Our study uses historical monthly workload figures (issues and receipts) over the past ten fiscal years (2004–2013). This gives us a suitable number of data points to analyze, with 120 data points in the series. DLA Operations Research and Resource Analysis (DORRA) provided us with ten years of issues and receipts broken down by month and by supply chain and service.

In addition to the data DORRA gave us, we recorded the O&M annual budgets for all ten years for analysis as a leading indicator of workload. The O&M budgets are what the services use to spend money, and buying supplies and parts from DLA is part of those expenditures. To narrow down the potential relationship, we only looked at four O&M Budget Activities: Operation and Maintenance, Operating Forces, Mobilization, and Operation Support. Purchases from DLA would generally originate from these funds.

To better understand the data, we graph the data points chronologically from October FY04 (October 2003 on our graphs) to September FY13 (September 2013 on our graphs) in Excel and analyze for trend patterns and seasonality. The software tool, JMP, also gives us good indicators of trend and seasonality through analysis of the autocorrelations. Once our understanding of the data series is sufficient, we decide on methods to forecast workload for the two-year PBR cycle that DLA sets.

2.   Determination of Forecasting Techniques

Based on the workload data we have as well as results from previous studies on forecasting techniques, we are using an ARIMA model as our primary technique but comparing this with three other techniques: double exponential smoothing (DES), moving average (MA) and linear regression. We are using an ARIMA model because it encompasses the concept of exponential smoothing with the autoregressive and moving average terms as well as accounting for trend (stationarity) and seasonality. Since our data series exhibits trend and seasonality an ARIMA model, although complicated, has the capacity to offer a refined, more detailed forecast. Since it is complicated, three ARIMA models are compared. The most commonly used seasonal ARIMA model, $(0,1,1)x(0,1,1)$ (Nau, 2014) is compared against two ARIMA models that we determine to best fit the data series and predict future values. Our best-fit determination is based on analysis of autocorrelations and selection of seasonal and non-seasonal AR and MA parameters facilitated by JMP's ARIMA Model Group tool that determines a best-fit model for the data series.

We compare our ARIMA models with a DES technique because DES is shown to be a good model. Gardner's 2006 study, as noted earlier, illustrates the effectiveness of a simple exponential smoothing technique in forecasting. In Orchowsky et al.'s summarization of previous study results, DES is shown to be a good technique used by DLA in the past. To compare complexity and simplicity further, we are also using a moving average technique. Moving average is one of the simplest forecasting methods, and was shown by the Boeing study to forecast Army and Navy data well.

Lastly, we are using a linear regression model with O&M dollars as the independent variable to deduce whether another leading indicator may replace and be better than sales. The assumption in this approach is that the services' O&M budget is a good representation of DLA's customer buying power.

To validate that our ARIMA model is a good fit for workload data and the complexity of it does actually improve the forecast, comparing it against these three other forecasting techniques is warranted.

3. Analysis and Comparison of the Models

We use JMP and Excel to help our analysis of each technique. The JMP tool can determine the coefficients for ARIMA, DES, and moving average parameters. The linear regression can just as easily be done in Excel. To determine this best model, comparison criteria are needed.

To compare the accuracy of the fitted ARIMA model with the other five, we measure forecast error by calculating MAD and MAPE. To compare precision and how well each model explains variation, we measure the coefficient of determination, R^2. Table 3 is completed in the Results section:

Model	MAD	MAPE	R^2
ARIMA (2,1,2)x(2,0,1)			
ARIMA (1,1,1)x(1,0,1)			
ARIMA (0,1,1)x(0,1,1)			
DES			
MA			
O&M Regression			
Current Regression			

Table 3.   Model comparison matrix

From the results of our comparison, we select the best performing models and conduct a sensitivity analysis.

4. Sensitivity and Simulation Analysis

We select best-fit models based on the above criteria and analyze how well they forecast under various situations. We use back-casting and upward and downward spikes to determine how well our selected models perform. Since DLA Distribution uses a two-year cycle (PBR cycle) to set rates and staffing targets, we back-cast two years.

We analyze an incremental approach with back-casting. Starting with the first three years of data, called the training set (Hyndman, 2010), we incrementally include another year for each iteration as we back-cast for the following two years, called the test

set (Hyndman, 2010). For example, in FY07 we use training set data from FY04–FY06 and predict FY08 and FY09. The next iteration includes four years of data and predicts FY09 and FY10. This is done until we reach the last two years of data, FY12 and FY13.

We look at our accuracy and precision criteria again and determine the confidence level of our models in predicting workload. When comparing the forecasted values with actual values in the test set, we use average error and percent error of aggregated yearly workload instead of MAD and MAPE, since DLA Distribution uses an aggregated yearly workload value to plan with. Based on forecast result accuracy, through average error and percent error comparison, we select the best three models for further analysis.

To simulate future changes and determine how our selected models react to a future that does not look like the past, we develop two scenarios: an uptick in issues and receipts over the next four years and a downtick utilizing the existing down-trending data. We use the absolute value of the four largest annual percent changes in workload over the data series as a basis for a simulated uptick and allocate the simulated data across each month based on historical monthly allocation percentage. We examine the down trending data from FY10 through FY13. Analysis of each scenario will determine whether our models are still performing well. Again, we compare these final three models by average error and percent error over the two-year PBR cycle portion of the test set, and select the best model.

Finally, we compare our forecast numbers from our selected model to the current model's forecasted numbers and see what would have been reported if our model was used. To do this, we replace the actual workload values with the actual workload values we used from DORRA and re-run the current regression model to determine the predicted workload. This allows us a comparison between what the current model predicted and what our proposed model predicts.

B.   PRESENTATION OF RESULTS

The result is a range of workload values that our model predicts within the confidence limits. The risks associated with values on the periphery of the confidence limits relate to staffing levels, spending plans, and rate-setting. We use the selected model

and predict workload for the next two years and use those figures to walk through the process of determining FTE requirements and potential savings that may occur.

We present our findings to DLA Distribution and explain the risk factors associated with this forecast and any forecast. Their decisions need to account for the risk of a model not being 100% accurate. Ultimately, the goal is to provide DLA with a practical model.

C. SUMMARY

This chapter described the relevant data we used in building a workload forecasting model for DLA Distribution and how we determined the four forecasting techniques used. A comparison of the techniques is described using the criteria of MAD, MAPE, and R^2 to determine the best model. Lastly, we described testing how well our forecast model performs by using back-casting and future workload scenarios. The next chapter will present the results of this methodology.

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IV. ANALYSIS AND RESULTS

This chapter describes our analysis of the data series and results of implementing the described methodology. Through test and comparison of forecasting models, we reach a final forecast model to compare with the current DLA regression model the workload values that would have been forecast if our model was used.

A. DATA ANALYSIS

1. Describing the Data

The monthly workload data used to conduct our analysis was gathered from an analyst at DORRA. The data has service workload broken down among Navy, Army, Air Force, Marines, DLA, and Other. Within each service, data was further broken down among the supply chains, where the workload data was identified as a receipt or issue. We conducted analysis using consolidated monthly workload, which accounted for receipts and issues amongst all supply chains and services. The data consisted of 131 data points and 13 complete fiscal years from October 2003 to August 2014. Analysis comparing fiscal years does not include FY14, because we did not have September 2014 data. When appropriate, however, we utilized all the data points available. From FY2000 to 2003 we were only able to account for total yearly workload numbers, because monthly data was not available. These data points were not used in our forecast modeling, but the yearly values provided us with supporting evidence used to conduct our sensitivity analysis.

DORRA's issues and receipts used in our analysis are slightly larger than the receipts and issues used by DLA in the existing model, as seen in Table 4. DORRA's numbers consider gross issues and receipts, while DLA's numbers are adjusted for specific coded lines that are not part of DLA Distribution's net landed cost model. Since we consistently use DORRA numbers throughout the analysis, our models are suitable for forecasting workload over PBR cycles.

Issue and Receipt Comparison			
Year	DORRA	DLA	DORRA's percentage difference
2010	22,706,614	21,636,406	+4.9%
2011	21,204,852	20,871,565	+1.6%
2012	19,429,227	18,433,148	+5.4%
2013	17,013,701	15,801,816	+7.7%

Table 4. DORRA vs DLA issue and receipt number differences

The graphs in Figures 3 through 8 represent DLA Distribution's workload (WL) profile based on proportion of total and service specific issues and receipts. Our issues and receipts requisitions are counted based on the customer and not classified by the service owner. For example, stock owned by DLA but requisitioned by the Army will be counted as an Army issue, not a DLA receipt. Figure 3 shows the issues and receipts by service.
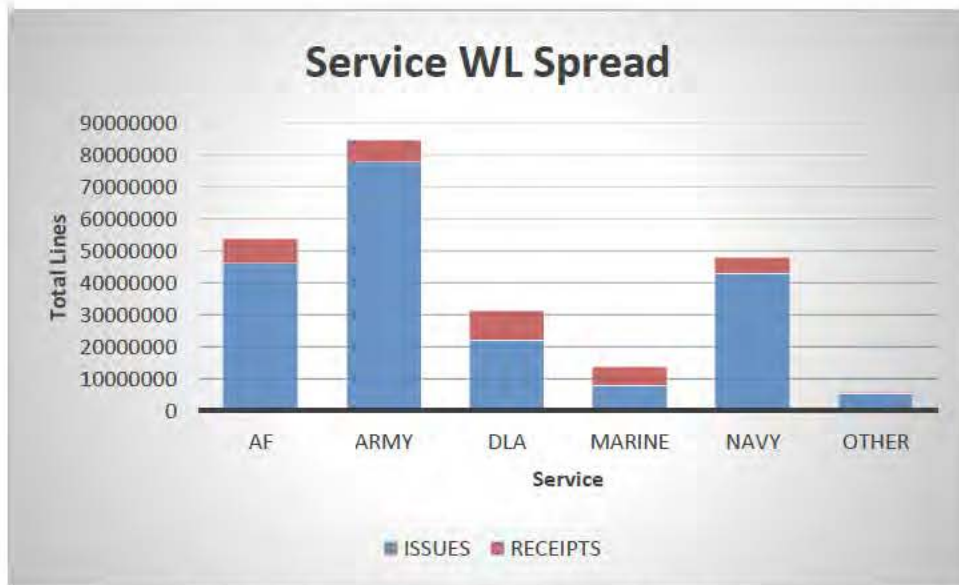
Figure 3. Issues and receipts by service

Figure 4 depicts the allocation of workload as a percentage to each service over an 11-year period. Army's workload matches best with the trend of DLA's total workload and represents the decline in total workload where deployments and budgets shrunk. The Navy and Air Force workload as a percentage, however, remained relatively constant over time.

30
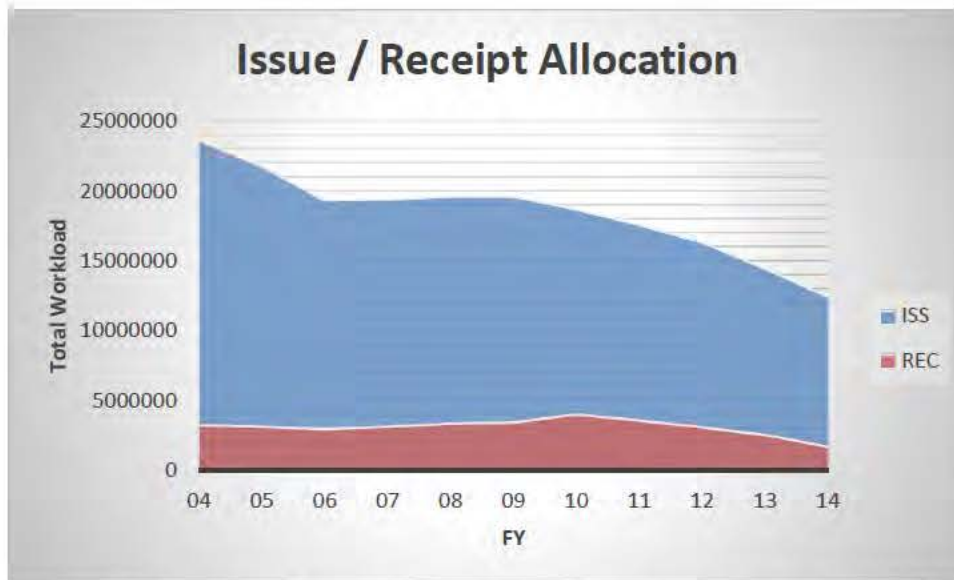
Figure 4.   Issue and receipt allocation 2004–2014

Figure 5 displays the yearly supply chain workload from fiscal year 2004 to fiscal year 2014. Industrial Hardware (IH) is a newly recognized supply chain that did not create additional DLA line items. The line items within the newly formed supply chains were reclassified from existing supply chains. Except for IH, the aviation supply chain was the only supply chain to show a significant change. Aviation's workload reduced at a much larger rate than all other supply chains from 2011 to 2014. Aviation went from 31% to 23% of DLA's total workload in three years. This significant change could be related to the reduction of overseas contingency operations or due more in part to the items being reclassified into IH.
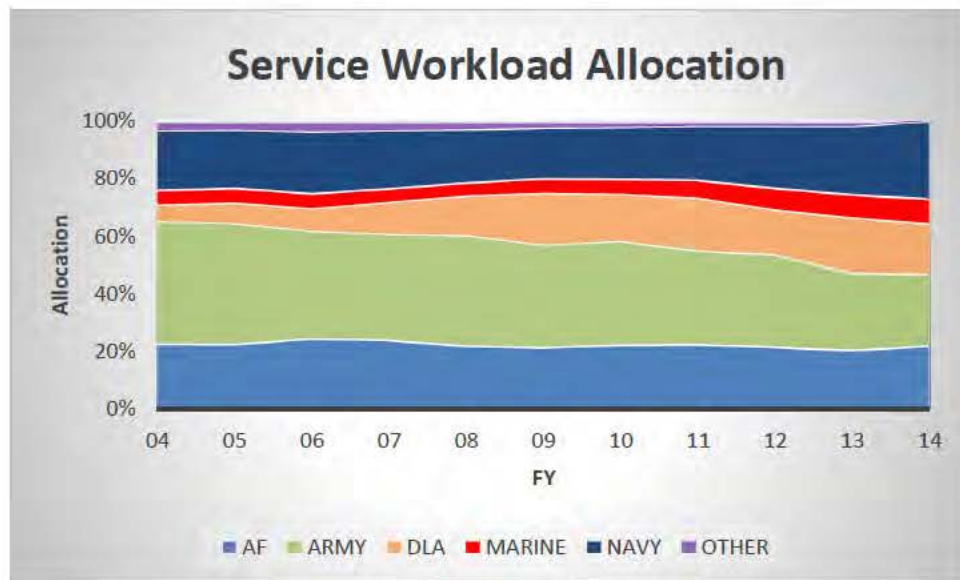
Figure 5.   Total workload allocation by Service percentage

Figure 6 displays the total workload percentage for each supply chain during FY14, excluding August. Four supply chains represent over 70% of DLA's workload. These four supply chains: Maritime, Land, Aviation, and IH, have a large influence on DLA's total workload. Therefore, understanding the causes of workload within these supply chains could result in a better understanding of DLA future total workload.
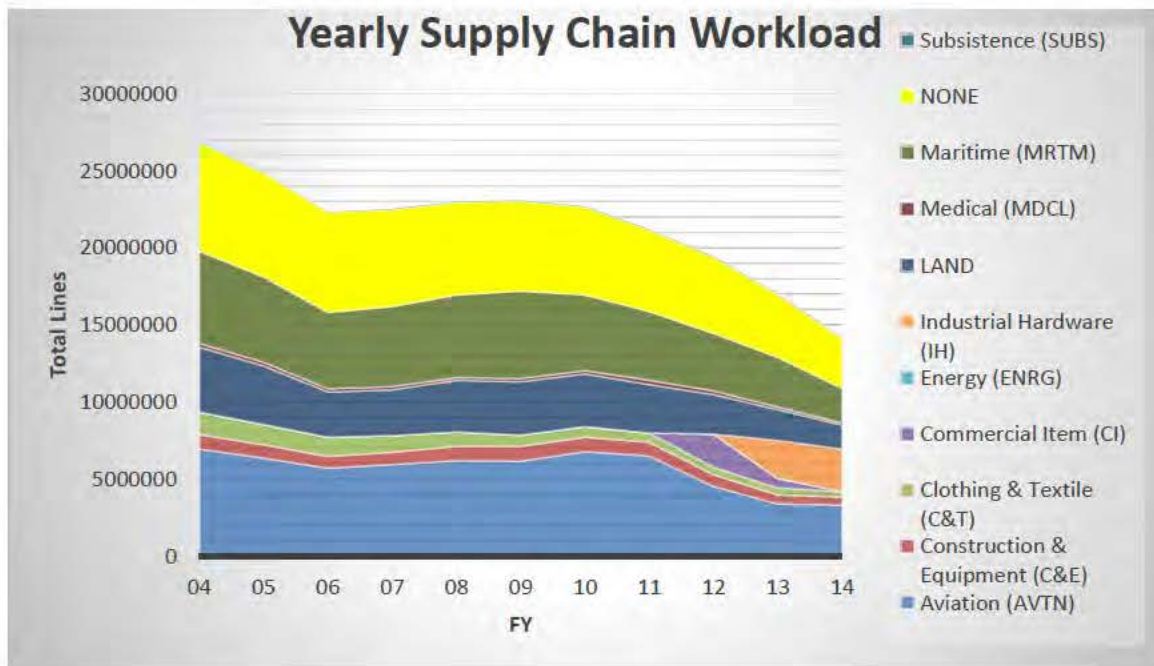
Figure 6.   Total workload allocated by supply chain 2004–2014

Figure 7 displays the historic average monthly allocation provided from 10 years of data. The monthly standard deviation is calculated and presented in the chart below the graph, which displays a minimal monthly variation from year to year. The linear trend line represented by the blue dotted line demonstrates an upward trend of workload throughout any given year. The upward trend is a result of the DOD quarterly spending process.

Finally, Figure 8 shows the historic monthly workload allocation between 2004 and 2014.
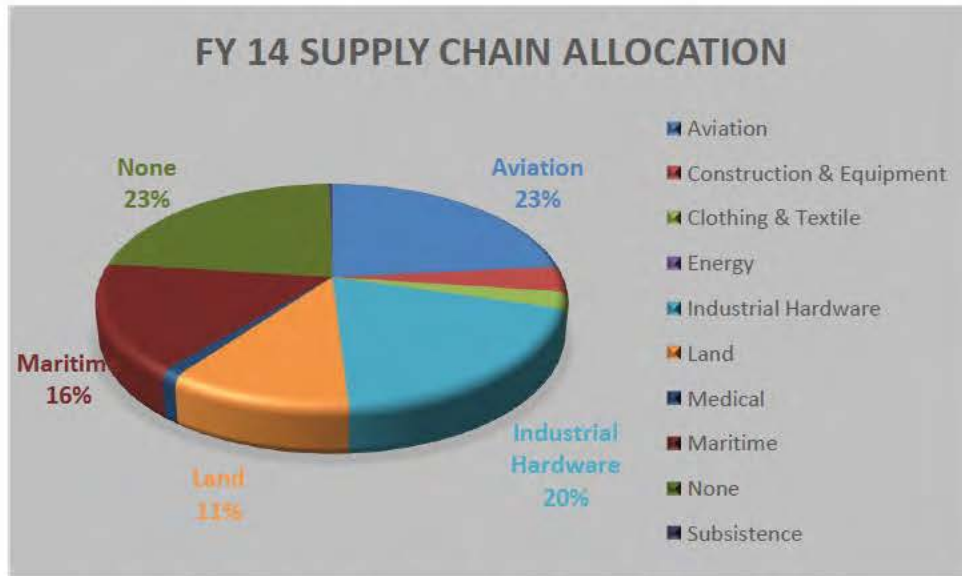
Figure 7.   FY14 workload allocation by supply chain

	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP
AVERAGE	8.25%	7.79%	7.77%	7.94%	8.08%	9.09%	8.71%	8.53%	8.30%	8.11%	9.01%	8.42%
STD DEV	0.63%	0.32%	0.29%	0.19%	0.30%	0.50%	0.32%	0.41%	0.31%	0.34%	0 36%	0.22%
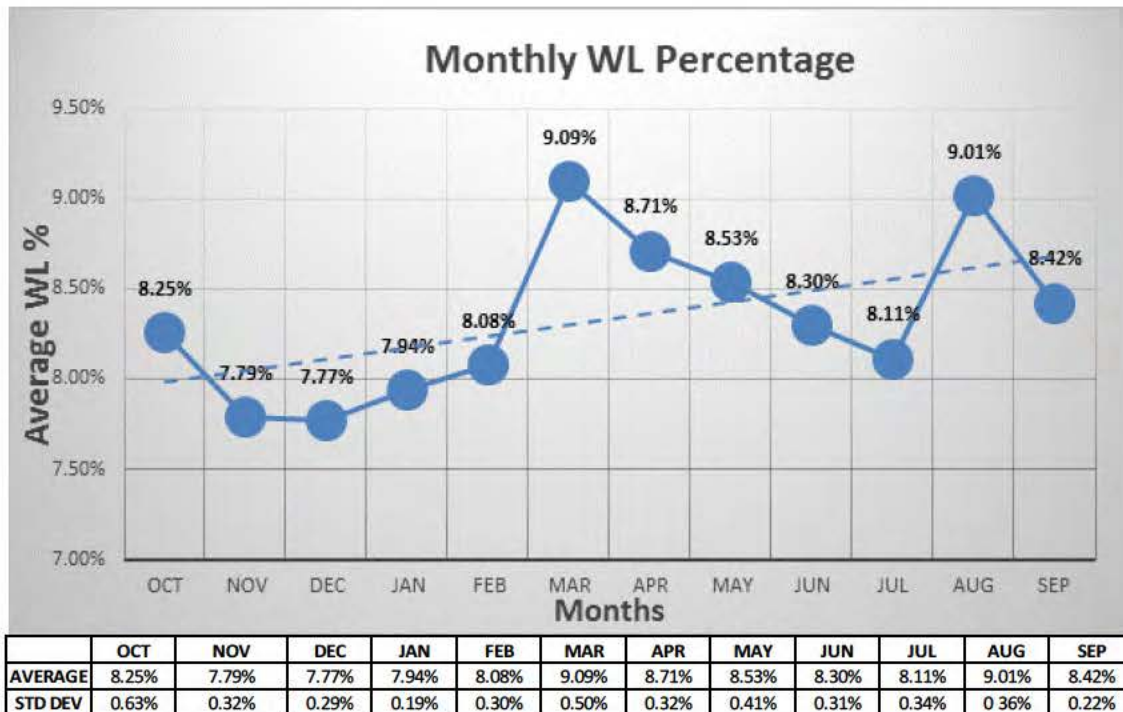
Figure 8.   Historic monthly workload allocation 2004–2014

B.   MODEL FIT

1.   Model Description

In additional to describing the models, we included the JMP software outputs, which contain the model summary, parameter estimates, and forecast graphs of our models.

a.   *ARIMA (2,1,2)x(2,0,1)12*

The following describes the process we used to appropriately fit the available data to each ARMIA model.

(1)   Set value for "d"

We first recognized a downward trend in the data as shown below by the data series and auto correlation plots (Figures 9 and 10).
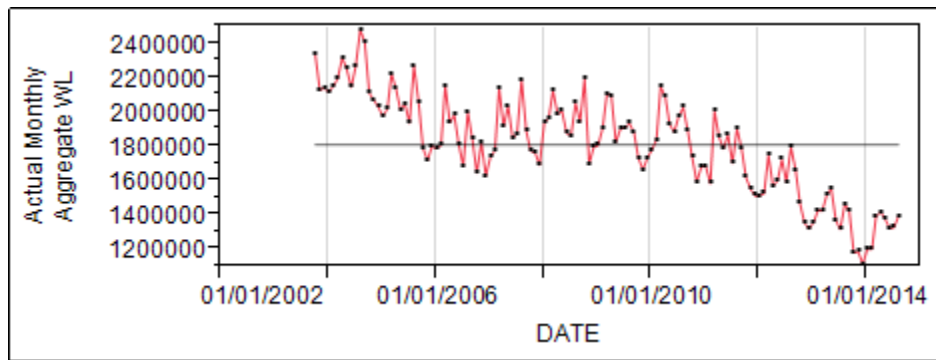
Figure 9.   Monthly workload data series graph

Lag	AutoCorr	-.8-.6-.4-.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value
0	1.0000		.	.
1	0.8363		93.7365	<.0001*
2	0.7523		170.180	<.0001*
3	0.6883		234.674	<.0001*
4	0.6446		291.679	<.0001*
5	0.6573		351.427	<.0001*
6	0.6311		406.943	<.0001*
7	0.5916		456.126	<.0001*
8	0.5385		497.194	<.0001*
9	0.5230		536.252	<.0001*
10	0.5110		573.848	<.0001*
11	0.5451		616.995	<.0001*
12	0.5780		665.915	<.0001*
13	0.4678		698.232	<.0001*
14	0.3965		721.642	<.0001*
15	0.3206		737.079	<.0001*
16	0.2793		748.894	<.0001*
17	0.3132		763.886	<.0001*
18	0.2648		774.695	<.0001*
19	0.2429		783.876	<.0001*
20	0.1956		789.884	<.0001*
21	0.1716		794.545	<.0001*
22	0.1832		799.911	<.0001*
23	0.2266		808.197	<.0001*
24	0.2461		818.062	<.0001*
25	0.1918		824.106	<.0001*
26	0.1384		827.286	<.0001*
27	0.0811		828.386	<.0001*
28	0.0675		829.158	<.0001*
29	0.1063		831.089	<.0001*
30	0.0682		831.891	<.0001*

Figure 10.   Workload data series autocorrelations

To make the data stationary, we added a first difference transformation (d). The subsequent residual graph (Figure 11) and differencing auto correlation plots (Figure 12) show data stationarity.
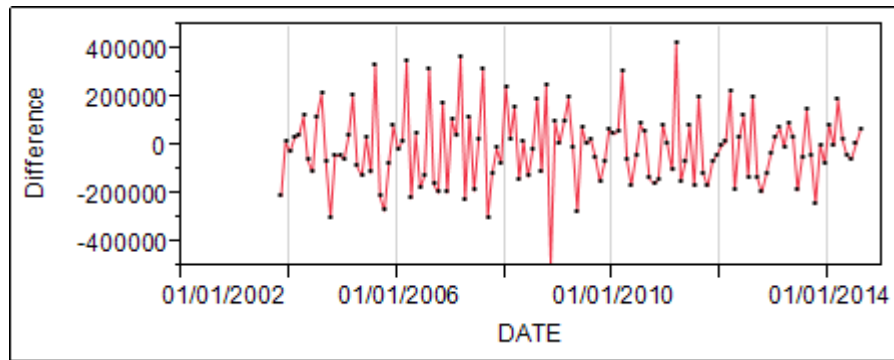
Figure 11.   Differenced residual graph

Lag	AutoCorr	-.8 -.6 -.4 -.2 0 .2 .4 .6 .8	Ljung-Box Q	p-Value
0	1.0000		.	.
1	-0.2546		8.6242	0.0033*
2	-0.0754		9.3856	0.0092*
3	-0.0608		9.8853	0.0196*
4	-0.2003		15.3504	0.0040*
5	0.1241		17.4636	0.0037*
6	-0.0028		17.4647	0.0077*
7	0.0559		17.8999	0.0124*
8	-0.1277		20.1951	0.0096*
9	-0.0255		20.2874	0.0162*
10	-0.2021		26.1291	0.0036*
11	0.0457		26.4299	0.0056*
12	0.5566		71.4834	<.0001*
13	-0.1512		74.8372	<.0001*
14	0.0281		74.9540	<.0001*
15	-0.0883		76.1180	<.0001*
16	-0.2772		87.6829	<.0001*
17	0.2389		96.3507	<.0001*
18	-0.0797		97.3229	<.0001*
19	0.0988		98.8328	<.0001*
20	-0.0945		100.225	<.0001*
21	-0.1033		101.904	<.0001*
22	-0.1551		105.726	<.0001*
23	0.1442		109.060	<.0001*
24	0.3224		125.892	<.0001*
25	-0.0194		125.953	<.0001*
26	0.0170		126.001	<.0001*
27	-0.1690		130.758	<.0001*
28	-0.1919		136.955	<.0001*
29	0.2334		146.212	<.0001*
30	-0.1187		148.629	<.0001*

Figure 12.   Differenced data autocorrelations

(2) Set value for "D"

The auto correlation plots from the differenced data supports our findings that our data does have seasonality (Figure 12). In particular, every 12 months or periods there is correlation between the same months from a previous year. Therefore, we use a 12-period season in our ARIMA model. Additionally, the data series exhibits no trend to the seasonal pattern, which is supported by the differenced data graph (Figure 11). Consequently, the seasonal differencing order (D) is zero.

(3) Set AR and MA parameters ("p,q and P,Q")

The autocorrelation and partial auto correlation plots for the differenced data do not provide a clear signature of the number of AR or MA parameters needed. There is no evidence from analysis of autocorrelations, however, to suggest more than 2 AR or MA seasonal and non-seasonal parameters (Figure 12). Additionally, too many parameters may lead to a perfect fit of the original time series, but may be a poor predictor of future values (Nau, 2014). Using the ARIMA Group model function from JMP, we determined that our best-fit model, based on an R^2 of .868, was ARIMA (2,1,2) x (2,0,1)12. Figures 13 through 15 illustrate the R^2, MAD, and MAPE of this ARIMA model as well as parameter value estimates, and show a graph of the model's outputs, with the red line showing the predicted values and the blue lines on either side showing the confidence interval.

Model Summary

DF	122	Stable	Yes
Sum of Squared Errors	1.0773e+12	Invertible	Yes
Variance Estimate	8830020772		
Standard Deviation	93968.1902		
Akaike's 'A' Information Criterion	3382.4913		
Schwarz's Bayesian Criterion	3405.43158		
RSquare	0.86767898		
RSquare Adj	0.86008679		
MAPE	4.21985815		
MAE	77084.6644		
-2LogLikelihood	3366.4913		

Figure 13.   R2, MAD (MAE), and MAPE for ARIMA (2,1,2)x(2,0,1)12

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant
AR1,1	1	1	0.434	0.016	26.78	<.0001*	**Estimate**
AR1,2	1	2	0.117	0.0041263	28.41	<.0001*	-0.0058436
AR2,12	2	12	1.280	1.6221e-6	788860	<.0001*	
AR2,24	2	24	-0.280	3.4429e-7	-8e+5	<.0001*	
MA1,1	1	1	1.108	0.030	36.54	<.0001*	
MA1,2	1	2	-0.234	0.012	-20.27	<.0001*	
MA2,12	2	12	0.998	0.0005488	1818.8	<.0001*	
Intercept	1	0	-8100.666	9494.890	-0.85	0.3952	

Figure 14.   Parameter estimates for p,q,P,Q for ARIMA (2,1,2)x(2,0,1)12
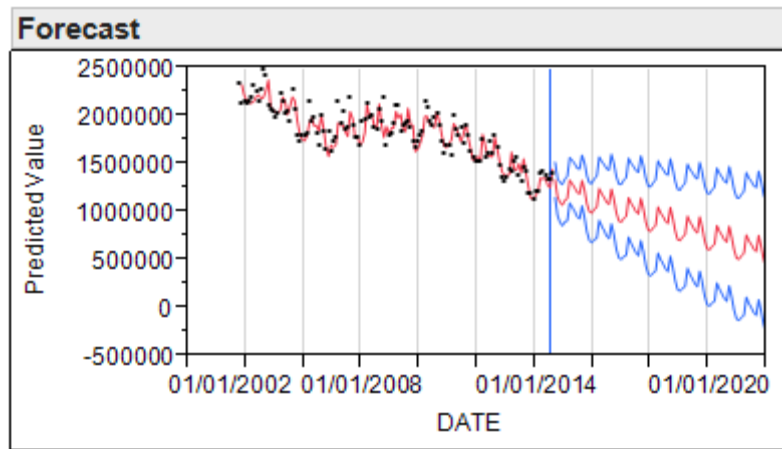
Figure 15.   Forecast graph for ARIMA(2,1,2)x(2,0,1)12

b.   *ARIMA (0,1,1)x(0,1,1)12*

We conducted further testing with more than one ARIMA model because the level of fitness depicted by R^2 is not always a good predictor of future data. We chose ARIMA (0,1,1)x(0,1,1)12 because it is one of the most common seasonal ARIMA models used (Nau, 2014). Figures 16 through 18 illustrate the R^2, MAD, and MAPE of this ARIMA model as well as parameter value estimates, and show a graph of the model's outputs.

Model Summary

DF	115	Stable	Yes
Sum of Squared Errors	9.9116e+11	Invertible	No
Variance Estimate	8618766270		
Standard Deviation	92837.3108		
Akaike's 'A' Information Criterion	3066.50131		
Schwarz's Bayesian Criterion	3074.81337		
RSquare	0.83922819		
RSquare Adj	0.83643216		
MAPE	4.31113732		
MAE	76859.4029		
-2LogLikelihood	3060.50131		

Figure 16.   R2, MAD (MAE), and MAPE for ARIMA (0,1,1)x(0,1,1)12

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant
MA1,1	1	1	0.6567	0.0688	9.54	<.0001*	**Estimate**
MA2,12	2	12	1.0000	0.2756	3.63	0.0004*	-184.74476
Intercept	1	0	-184.7448	931.1324	-0.20	0.8431	

Figure 17.   Parameter estimates for p,q,P,Q for ARIMA (0,1,1)x(0,1,1)12
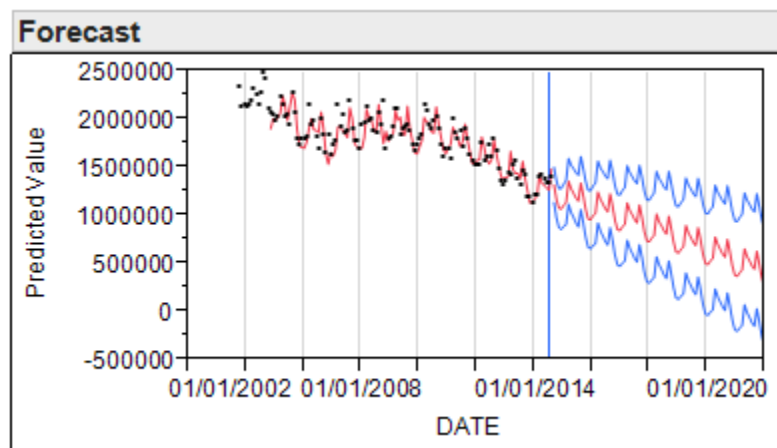
Forecast

Figure 18.   Forecast graph for ARIMA(0,1,1)x(0,1,1)12

c.   *ARIMA (1,1,1)x(1,0,1)12*

The third model chosen was ARIMA (1,1,1)x(1,0,1)12 because it took our original model and simplified it by removing AR and MA terms that could be over-fitting the data, but without losing seasonality for future values. Figures 19 through 21 illustrate

the R^2, MAD, and MAPE of this ARIMA model as well as parameter value estimates, and show a graph of the model's outputs.

Model Summary

DF	125 Stable Yes
Sum of Squared Errors	1.087e+12 Invertible Yes
Variance Estimate	8695658209
Standard Deviation	93250.5132
Akaike's 'A' Information Criterion	3384.67746
Schwarz's Bayesian Criterion	3399.01513
RSquare	0.85850298
RSquare Adj	0.85397507
MAPE	4.36744977
MAE	80088.1302
-2LogLikelihood	3374.67746

Figure 19.   R2, MAD (MAE), and MAPE for ARIMA (1,1,1)x(1,0,1)12

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant
							Estimate
AR1,1	1	1	-0.067	0.0137489	-4.90	<.0001*	
AR2,12	2	12	1.000	8.1387e-7	1.2e+6	<.0001*	-0.0041645
MA1,1	1	1	0.606	0.0666714	9.10	<.0001*	
MA2,12	2	12	0.999	0.0003128	3192.4	<.0001*	
Intercept	1	0	-8060.197	12898.24	-0.62	0.5332	

Figure 20.   Parameter estimates for p,q,P,Q for ARIMA (1,1,1)x(1,0,1)12
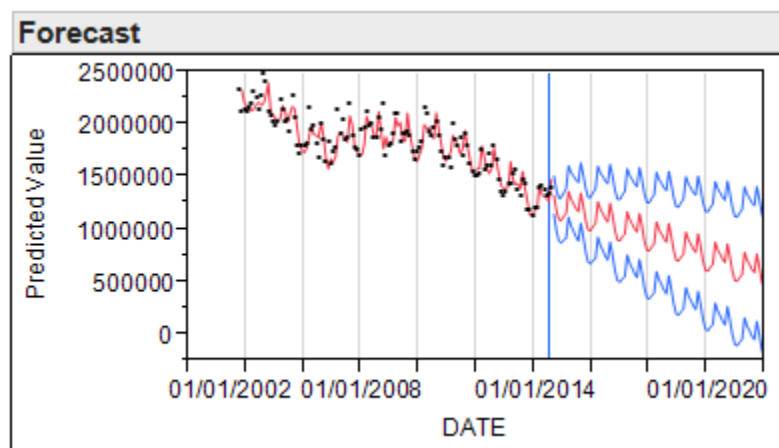
Figure 21.   Forecast graph for ARIMA(1,1,1)x(1,0,1)12

d. DES

We used JMP to formulate appropriate coefficients for our DES model. Figures 22 through 24 illustrate the R^2, MAD, and MAPE of this DES model as well as parameter value estimates, and show a graph of the model's outputs.

Model Summary

DF	128	Stable	Yes
Sum of Squared Errors	2.9566e+12	Invertible	Yes
Variance Estimate	2.3099e+10		
Standard Deviation	151982.355		
Akaike's 'A' Information Criterion	3451.38877		
Schwarz's Bayesian Criterion	3454.24858		
RSquare	0.70533975		
RSquare Adj	0.70533975		
MAPE	7.03647011		
MAE	125778.062		
-2LogLikelihood	3449.38877		

Figure 22.   R2, MAD (MAE), and MAPE for DES

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.11940809	0.0334009	3.57	0.0005*

Figure 23.   Smoothing constant estimate for DES
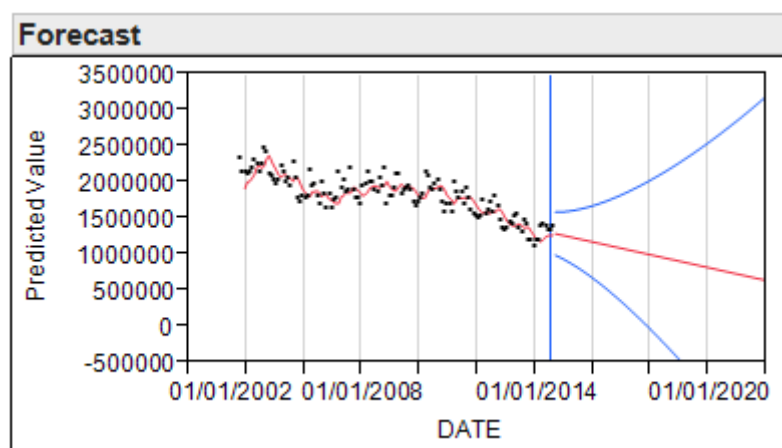
Figure 24.   Forecast graph for DES

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e. MA

We used a MA model to compare against our more complex models. In order to predict out far enough, we used 31 MA coefficients. Figures 25 through 27 illustrate the R^2, MAD, and MAPE of this MA model as well as parameter value estimates, and show a graph of the model's outputs.

Model Summary

DF	99	Stable	Yes
Sum of Squared Errors	1.2568e+12	Invertible	No
Variance Estimate	1.2695e+10		
Standard Deviation	112672.822		
Akaike's 'A' Information Criterion	3509.65464		
Schwarz's Bayesian Criterion	3601.66095		
RSquare	0.78851646		
RSquare Adj	0.72229434		
MAPE	5.44399009		
MAE	99667.8892		
-2LogLikelihood	3445.65464		

Figure 25.　R2, MAD (MAE), and MAPE for MA

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate
MA1	1	-0.3978894	0.1288023	-3.09	0.0026*	1799875.81
MA2	2	-0.4747813	0.111589	-4.25	<.0001*	
MA3	3	-0.3533395	0.0898838	-3.93	0.0002*	
MA4	4	-0.296745	0.0922315	-3.22	0.0017*	
MA5	5	-0.7791303	0.1293497	-6.02	<.0001*	
MA6	6	-0.2233778	0.1314175	-1.70	0.0923	
MA7	7	-0.4205171	0.204092	-2.06	0.0420*	
MA8	8	0.01124107	0.0285673	0.39	0.6948	
MA9	9	-0.5880831	0.1632486	-3.60	0.0005*	
MA10	10	0.11056503	0.09786	1.13	0.2613	
MA11	11	-0.5259102	0.1809615	-2.91	0.0045*	
MA12	12	-0.5945874	0.1330624	-4.47	<.0001*	
MA13	13	-0.8109793	0.1897731	-4.27	<.0001*	
MA14	14	-0.7466476	0.152729	-4.89	<.0001*	
MA15	15	-0.597989	0.2454064	-2.44	0.0166*	
MA16	16	-0.547467	0.1439805	-3.80	0.0002*	
MA17	17	-0.8241105	0.1643952	-5.01	<.0001*	
MA18	18	-0.948677	0.1	-9.47	<.0001*	
MA19	19	-0.1826215	0.1316925	-1.39	0.1686	
MA20	20	-0.4970215	0.210187	-2.36	0.0200*	
MA21	21	0.03347745	0.08414	0.40	0.6916	
MA22	22	-0.4582956	0.244617	-1.87	0.0639	
MA23	23	-0.0542514	0.1162133	-0.47	0.6416	
MA24	24	-0.6035083	0.2654492	-2.27	0.0252*	
MA25	25	-0.2383143	0.1415312	-1.68	0.0954	
MA26	26	-0.6688635	0.2167167	-3.09	0.0026*	
MA27	27	-0.3381207	0.1762038	-1.92	0.0579	
MA28	28	-0.1253801	0.1154751	-1.09	0.2802	
MA29	29	-0.9409238	0.1862121	-5.05	<.0001*	
MA30	30	-0.4372291	0.1239651	-3.53	0.0006*	
MA31	31	-0.4820726	0.1582661	-3.05	0.0030*	
Intercept	0	1799876	117077.1	15.37	<.0001*	

Figure 26.   Parameter estimates for MA
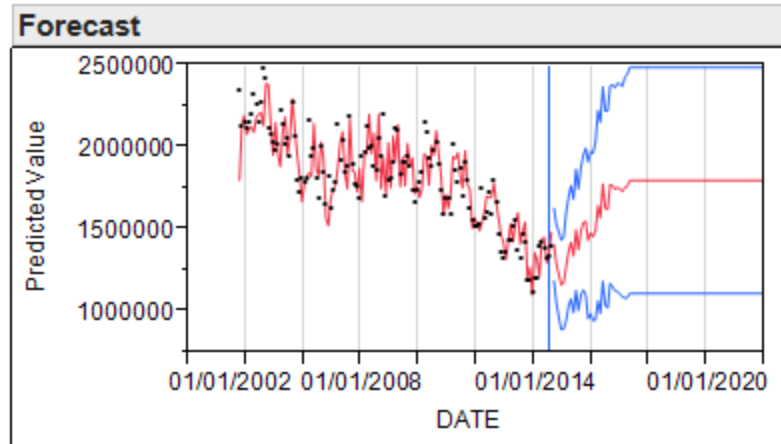
Figure 27.   Forecast graph for MA

f.   *Operation and Maintenance Budget and Workload Analysis*

(1)   Description of O&M Analysis

We analyzed O&M budget requests to determine if they could be used as a leading indicator to predict DLA distribution workload. DLA's primary customers are the Army, Navy, Air Force, and Marines. The services' "buying power" can be measured in terms of annual budgeted authorization. We presumed the amount DOD requested in O&M funding may reflect a change, either increase or decrease, in operational activity based on anticipated mission requirements. An example would be if the Air Force estimated an increase in flight hours for the next FY and request funding accordingly. An increase or decrease in flight hours results in logistical requirements that are then translated into additional or reduced workload for DLA Distribution.

We compiled O&M budgeting information from the Office of the Under Secretary of Defense Comptroller website for FY2006 to FY2013. We used the same aggregated FY issues and receipts provided by DORRA and used with our other model analysis. The O&M budget request contains funding for training, maintenance, administrative costs, and purchases from DWCF related to DLA for spare parts. The O&M budget includes payments to support allied forces and multiple other expenses that do not necessarily predict future operational activity. We included additional funding requests for overseas contingency operations (OCO) or for the Global War on Terrorism

not included in the base budget request. We further narrowed our analysis to a single budget activity, Operating Forces, which we believe would be the most relevant indicator to change in the DOD's "buying power" and demand on DLA Distribution.

(2)   Results

Over the past eight years, O&M funding requests have increased and decreased due to changing operational needs. DLA's workload did not reflect a reaction to the change in funding (Figure 28).
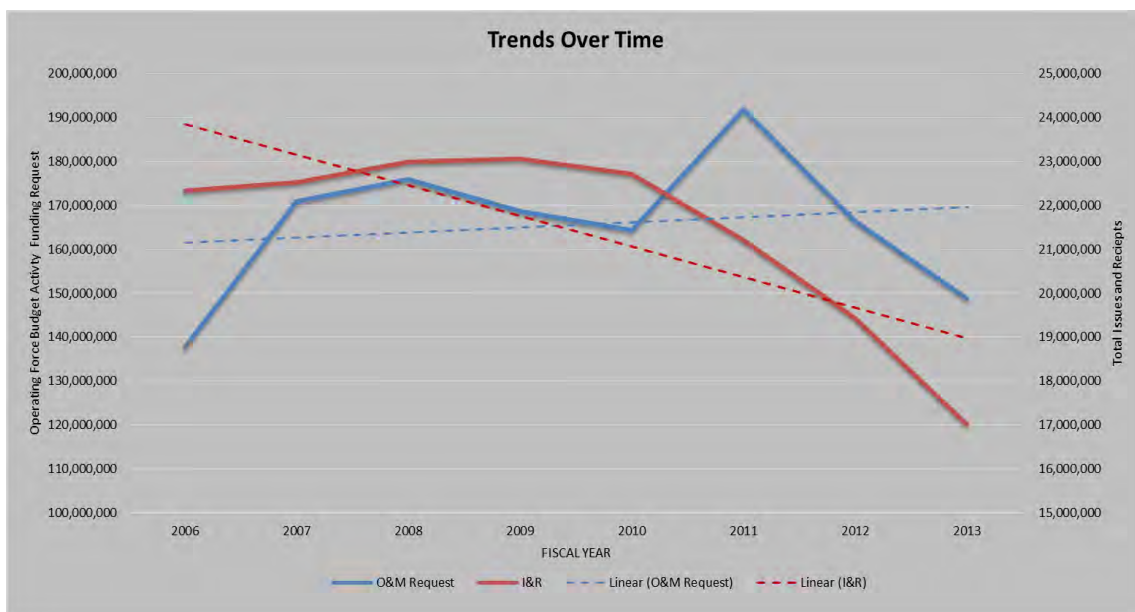
Figure 28.   Comparing O&M budget requests against FY total issues and receipts

The trend lines in Figure 28 show increases in O&M, which do not reflect an increase in DLA workload. We further attempted to test the data by conducting a simple linear regression and trying to predict the future FY DLA workload (Figure 29).
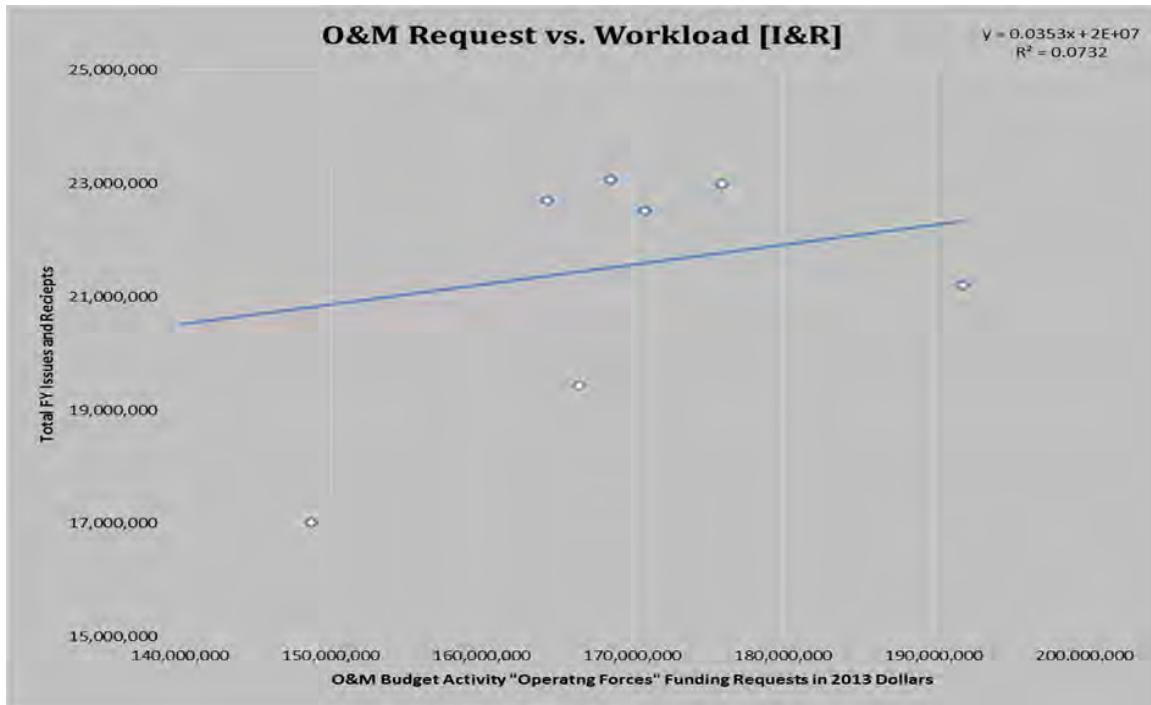
Figure 29.   O&M vs. I&R regression

The resulting model's R^2 was .0732. The model predicted FY2013 workload of 20,812,990, which resulted in a 3,799,289 MAD (over prediction), and a 22.3% MAPE.

(3)   O&M Conclusion

The analysis showed O&M budget requests do not provide a leading indicator to predict changes in DLA Distribution workload. In fact, DLA Distribution workload continued to show a downward trend without regard to the changing O&M budget requests.

2.   Model "Best-Fit" Comparison Based on All Data

The model comparison matrix in Figure 30 shows the accuracy and precision criteria used to determine the best-fit model for our workload data series.

MODEL	R^2	MAD	MAPE
ARIMA (2,1,2) x (2,0,1)12	0.868	77,084	4.22%
ARIMA (1,1,1) x (1,0,1)12	0.856	80,088	4.37%
ARIMA (0,1,1) x (0,1,1)12	0.839	76,859	4.31%
MA	0.789	99,668	5.44%
DES	0.705	125,778	7.04%
O&M vs. WL Regression Model	0.073	316,607	22.30%
DLA Linear Regression Model	0.019	158,421	13.31%

Figure 30.   "Best fit" model comparison matrix

From these results, the ARIMA models performed best, followed by DES and MA. Using a threshold of $R^2 => 0.50$, we remove the two regression models from further analysis.

C.   FORECAST COMPARISON

1.   PBR Cycle

Figure 31 explains the framework of how we conducted workload forecasting for a given PBR cycle under DLA's current PBR planning timeline. The PBR cycle forecast encompasses two fiscal years of monthly data points. For example, PBR 16 forecast would include data points from October 2014 until September 2016. The input data for the forecast period can start as early as October 2003, the earliest monthly data point, and include years up to the last data point ending on time period "T." Time period "T" represents the February prior to the start of the forecasted PBR cycle. In this example, time period "T" would be February 2014. Our model fit analysis focuses on the years of the input data time period, and our back-casting analysis focuses on the forecast predictions for a given PBR cycle.
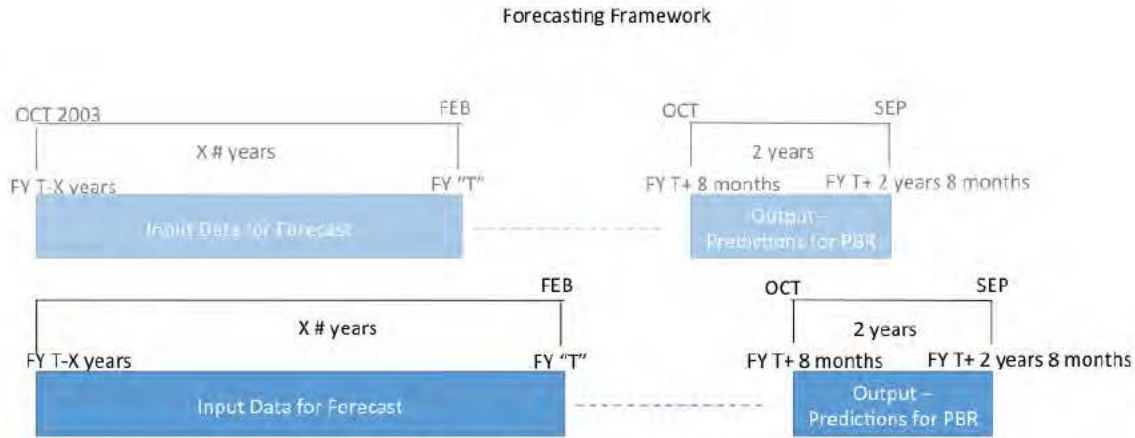
Figure 31.   DLA PBR cycle forecasting framework

2.   Back-Casting Results

a.   *Forecasting Error Minimums, Maximums, Average and Range*

Figure 32 depicts the minimum and maximum error for each model. The best error value in each column is colored green and the worst is colored red. Interestingly, the MA model produced the best overall minimum error in the first year but its maximum was also the highest. The poorest performing model was determined to be ARIMA (0,1,1)x(0,1,1)12, which consistently produced the highest minimums and maximums. The other two ARIMA models and DES were determined to be within the acceptable range based on relative comparable results.

	Minimum Error			Maximum Error		
	1st year	2nd year	2 Yr Average	1st year	2nd year	2 Yr Average
ARIMA (2,1,2) x (2,0,1)12	243,558	607,831	425,694	4,104,431	6,109,895	5,107,163
ARIMA (0,1,1) x (0,1,1)12	1,513,232	1,467,841	1,529,266	4,245,868	8,417,344	6,331,606
ARIMA (1,1,1) x (1,0,1)12	219,290	263,421	379,610	4,234,074	6,314,583	5,274,328
DES	390,419	199,699	552,305	4,531,780	6,643,888	5,587,834
MA	94,915	1,044,214	569,564	4,957,595	6,001,266	4,394,575

Figure 32.   Minimum and maximum error results for back-casting

We also examined the average errors and error range in predicting future workload. The MA model performed worst in the first year in both error categories. The

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poorest performing model was determined to be ARIMA (0,1,1)x(0,1,1)12, which produced the highest minimums and maximums. Again, the other two ARIMA models and DES were determined to be within the acceptable range based on relative comparable results (Figure 33).

	Average Error			Error Range		
	1st year	2nd year	2 Yr Average	1st year	2nd year	2 Yr Average
ARIMA (2,1,2) x (2,0,1)12	1,433,230	2,354,067	1,856,518	3,860,873	5,502,064	4,681,469
ARIMA (0,1,1) x (0,1,1)12	2,351,209	5,021,488	3,702,875	2,732,636	6,949,503	4,802,340
ARIMA (1,1,1) x (1,0,1)12	1,315,624	2,190,574	1,745,092	4,014,783	6,051,161	4,894,718
DES	1,441,219	1,868,292	1,739,440	4,141,361	6,444,189	5,035,529
MA	2,772,281	2,904,519	2,779,071	4,862,681	4,957,052	3,825,010

Figure 33.   Average error and error range results for back-casting

b.   *Forecasting Percent Error Minimums, Maximums, Average and Range*

Although the overall errors explain the total workload difference for each year, we used the percent error to provide a better estimate to compare each model. The poorest performing model was again determined to be ARIMA (0,1,1)x(0,1,1)12, which consistently produced the highest minimum and maximum percent error. MA performed best for the minimum percent error in the first year but also had the highest maximum first-year percent error (Figure 34).

	Minimum PE			Maximum PE		
	1st year	2nd year	2 Yr Average	1st year	2nd year	2 Yr Average
ARIMA (2,1,2) x (2,0,1)12	1.07%	2.87%	1.94%	17.85%	26.49%	22.18%
ARIMA (0,1,1) x (0,1,1)12	6.92%	6.36%	6.64%	18.41%	37.07%	27.67%
ARIMA (1,1,1) x (1,0,1)12	1.10%	1.20%	1.7%	18.4%	27.4%	22.9%
DES	1.72%	1.03%	2.65%	19.71%	28.81%	24.26%
MA	0.41%	4.60%	2.51%	26.25%	35.27%	24.81%

Figure 34.   Minimum and maximum percent error results for back-casting

ARIMA (0,1,1)x(0,1,1)12 and MA had the lowest performance when assessing both average percent error and percent error range. The other two ARIMA models performed the best while DES remained within close relative range (Figure 35).

	Average Percentage Error (PE)			PE Range		
	1st year	2nd year	2 Yr Average	1st year	2nd year	2 Yr Average
ARIMA (2,1,2) x (2,0,1)12	6.81%	10.72%	8.14%	16.8%	23.6%	20.2%
ARIMA (0,1,1) x (0,1,1)12	10.77%	24.36%	16.71%	11.5%	30.7%	21.0%
ARIMA (1,1,1) x (1,0,1)12	6.1%	10.1%	7.92%	17%	26%	21%
DES	6.67%	8.55%	7.93%	18.0%	27.8%	21.6%
MA	14.32%	15.16%	14.19%	25.8%	30.7%	22.3%

Figure 35. Average percent error and percent error range results for back-casting

3. Selection Decision (Model Down Select)

We selected ARIMA (2,1,2)x(2,0,1)12, ARIMA (1,1,1)x(1,0,1)12, and DES based on comparable relative performance during our back-casting analysis. The ARIMA (0,1,1)x(0,1,1)12 total error and percent error were the lowest-performing results and determined to be excluded from further analysis. The MA model performed relatively well. We determined to exclude MA from further analysis considering its large average 1st year total and percent error, and the largest percent error range. We assessed MA to be too inconsistent to result in a suitable forecast to make informed business decisions over a PBR cycle.

D. SENSITIVITY ANALYSIS

A sensitivity analysis enables us to determine how reactive our remaining models are to a change in workload (uptick or downtick). The actual workload experienced at DLA is already exhibiting a downtick, so we use that to measure the reacting ability of our models. We simulate an uptick to measure our models' reaction to a future change as well.

1.   Downtick in Actual Data from FY10 to FY13

We use data from FY04 to FY09 as the training set to forecast FY10 through FY13 (the test set) for ARIMA (2,1,2)x(2,0,1)12, ARIMA (1,1,1)x(1,0,1)12, and DES models and compare with the actual data from FY10 to FY13. We then add FY10 and analyze how each model adjusts to the change in workload starting in FY10, and measure the forecast ability for FY11–FY13. We continue adding an additional year to the forecast model, measuring the accuracy and precision of each model. The two-year PBR cycle of the test set is measured.

a.   *Sensitivity Analysis Results*

The downtick scenario results are depicted in Figures 36 through 38. Since part of our training set data had a downward trend, our models will not have a large percent error compared to our uptick scenario, which simulated a significant change in historical trend. Each graph has corresponding tables, which both represent the training set and test set summary data for each PBR cycle. The green box highlighted within each year of the PBR cycle represents the model that outperformed the other models based on percent error. ARIMA (1,1,1)x(1,0,1)12 displayed better results for the majority of the three downtick PBR cycles examined. No model, however, displayed results outside the relative acceptable range.
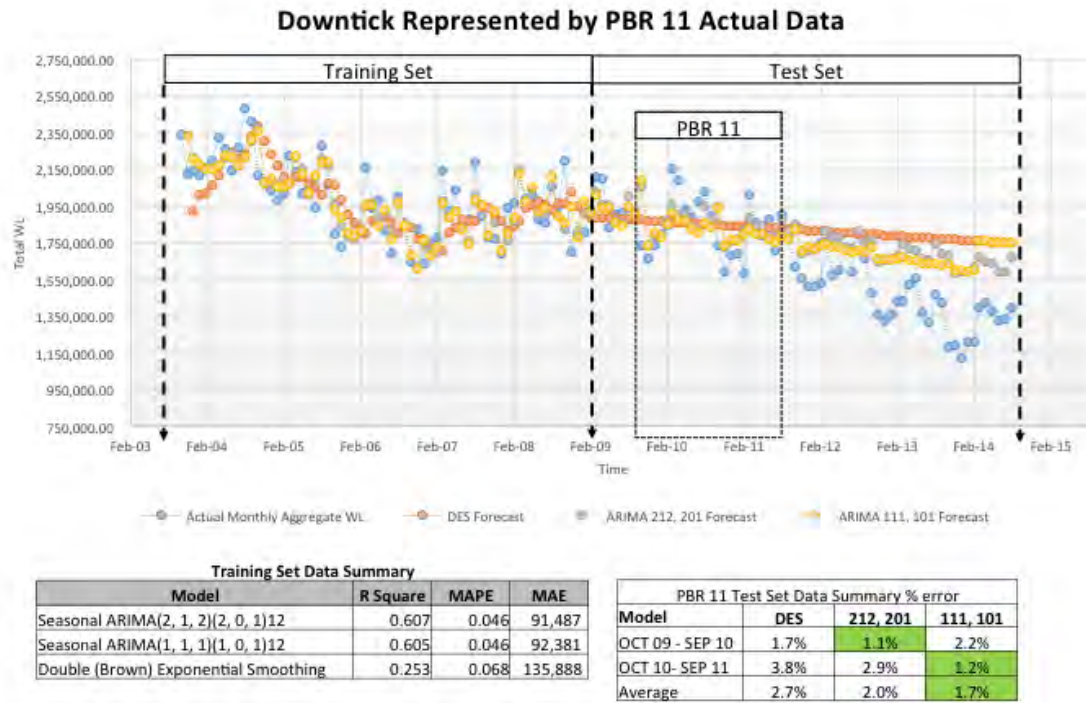
Figure 36.   Downtick scenario and forecast results for PBR 11

Downtick Represented by PBR 12 Actual Data

Training Set Data Summary

Model	R Square	MAPE	MAE
Seasonal ARIMA(2, 1, 2)(2, 0, 1)12	0.558	0.045	90,025
Seasonal ARIMA(1, 1, 1)(1, 0, 1)12	0.585	0.046	90,830
Double (Brown) Exponential Smoothing	0.273	0.066	130,107

PBR 12 Test Set Data Summary % error			
Model	DES	212, 201	111, 101
OCT 10 - SEP 11	4.27%	1.22%	1.15%
OCT 11 - SEP 12	1.03%	3.19%	3.21%
Average	2.65%	2.20%	2.18%
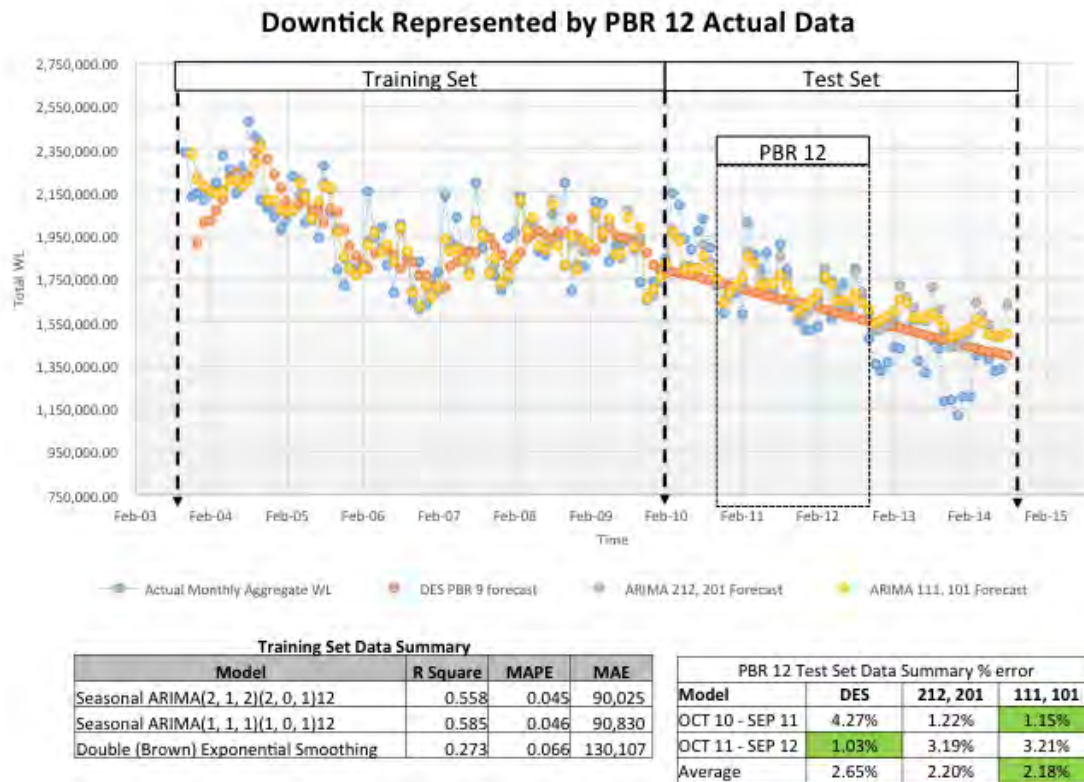
Figure 37.   Downtick scenario and forecast results for PBR 12

Downtick Represented by PBR 13 Actual Data

Training Set Data Summary

Model	R Square	MAPE	MAE
Seasonal ARIMA(2, 1, 2)(2, 0, 1)12	0.649	0.044	86,386
Seasonal ARIMA(1, 1, 1)(1, 0, 1)12	0.615	0.045	88,368
Double (Brown) Exponential Smoothing	0.272	0.068	132,071

PBR 13 Test Set Data Summary % error			
Model	DES	212, 201	111, 101
OCT 11 - SEP 12	7.54%	2.06%	1.13%
OCT 12- SEP 13	6.65%	11.93%	9.21%
Average	7.09%	7.00%	5.17%

Figure 38.   Downtick scenario and forecast results for PBR 13

2.   Simulated Uptick

The simulated data used for this scenario is based on the four highest absolute percent changes in annual workload, which are 8.4%, 9.6%, 10.3%, and 12.4%. Similar to the downtick scenario, we incrementally include the four years of simulated data in the forecast and measure how well our three models adjust to the change and forecast future values. The two-year PBR cycle of the test set is measured.

a.   *Uptick Results*

The uptick scenario results have a larger disparity between the compared models than the downtick scenario. The difference can be explained by the trend reversal simulated in the uptick scenario. As a whole, the training set data in the uptick scenario exhibits a downward trend from 2004 to the start of the simulated data, which will lead to 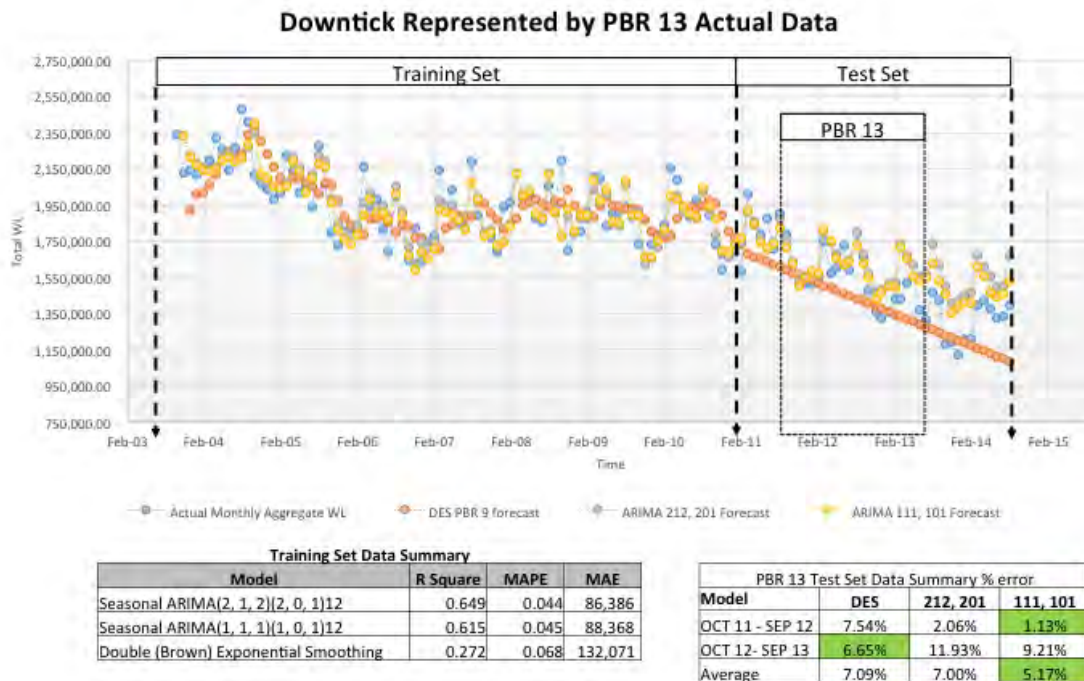forecast values that represent the same downward trend. Therefore, the forecasted values will reflect poor error values and will not represent an accurate forecast until enough simulated data is introduced in the training set.

In the first uptick graph (Figure 39), when only 5 months of simulated data is introduced to the training set, ARIMA (1,1,1)x(1,0,1)12 performs better than the other two models during PBR 16. These results could conclude ARIMA (1,1,1)x(1,0,1)12 possesses less risk during an initial trend change in workload, but the difference is not significant enough to support that claim.

Training Set Data Summary			
Model	R Square	MAPE	MAE
Seasonal ARIMA(2, 1, 2)(2, 0, 1)12	0.819	4.23%	81,181
Seasonal ARIMA(1, 1, 1)(1, 0, 1)12	0.802	4.60%	84,912
Double (Brown) Exponential Smoothing	0.628	6.76%	124,262

PBR 16 Test Set Data Summary % error			
Model	DES	212, 201	111, 101
OCT 14 - SEP 15	21.2%	14.8%	14.5%
OCT 15 - SEP 16	33.1%	27.0%	26.5%
Average	27.2%	20.9%	20.5%
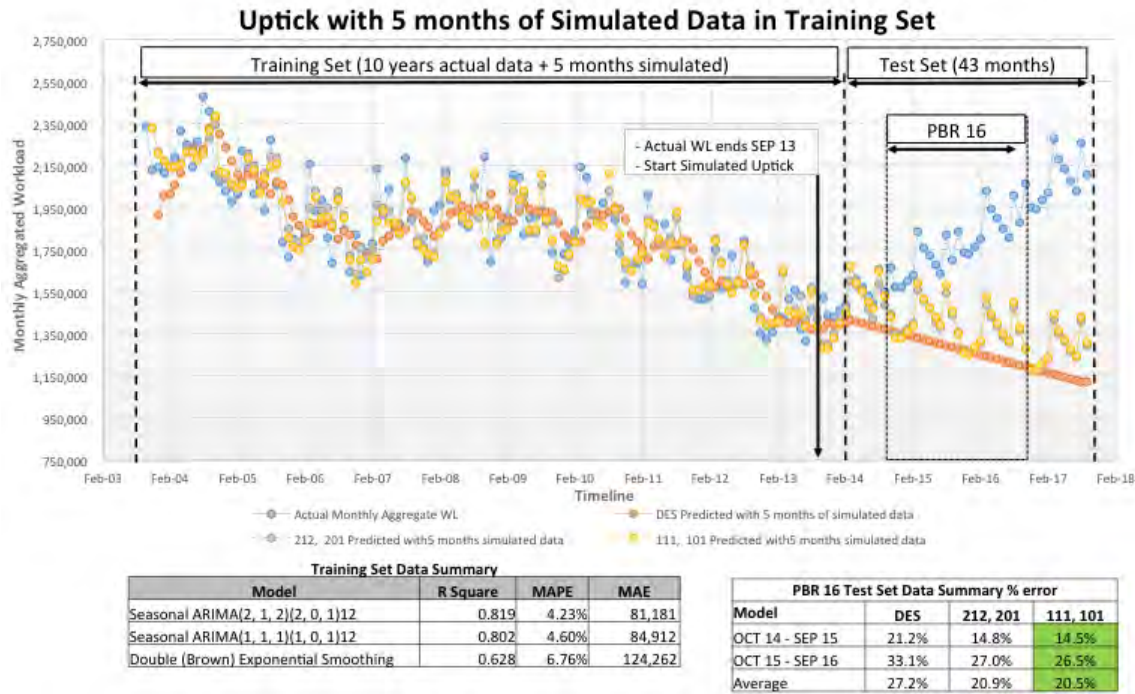
Figure 39. Uptick scenario and forecasting results with 5 months simulation data introduced

DES performs exceptionally better than the other two models in the second uptick graph, PBR 17 (Figure 40), which has 17 months of simulated data. ARIMA (2,1,2)x(2,0,1)12 performs worst during that same time period.

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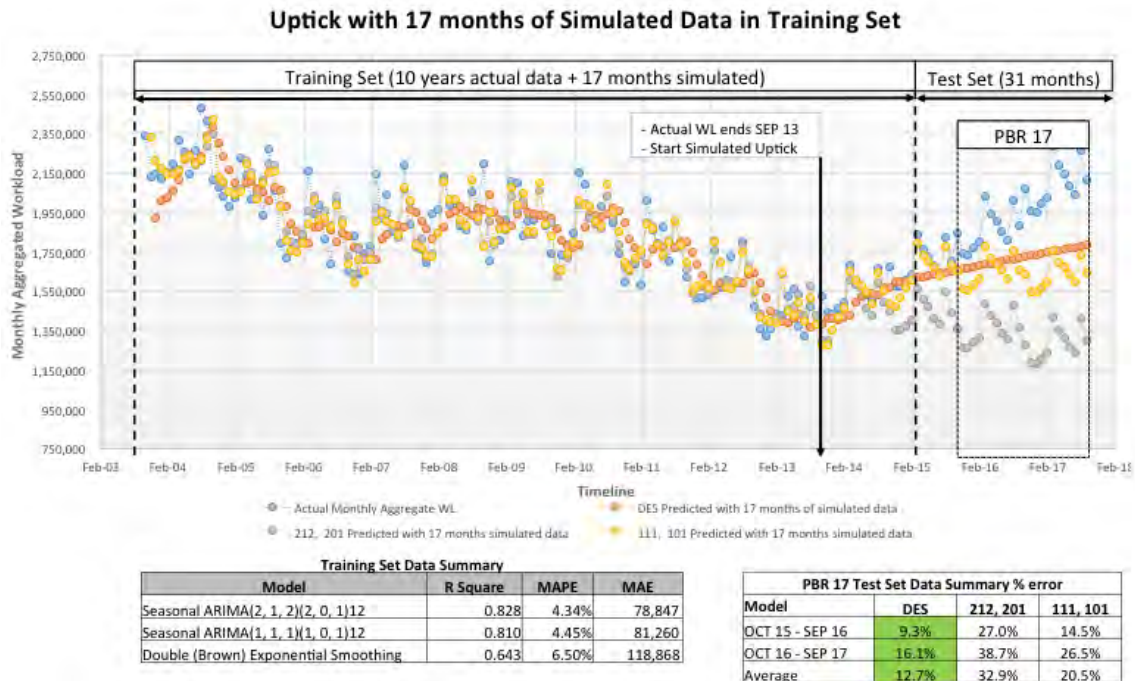
Figure 40.   Uptick scenario and forecasting results with 17 months simulation
data introduced

During PBR 18, where 29 months of simulated data is introduced to the training set data, DES performs better, but the remaining models are not far behind. ARIMA (2,1,2)x(2,0,1)12 is less reactive in a changing environment, while DES is very sensitive to changing training set data. There are advantages and disadvantages to both, but ARIMA (1,1,1)x(1,0,1)12 is moderately reactive and provides less risk in an uncertain environment, where the future is unknown (Figure 41).
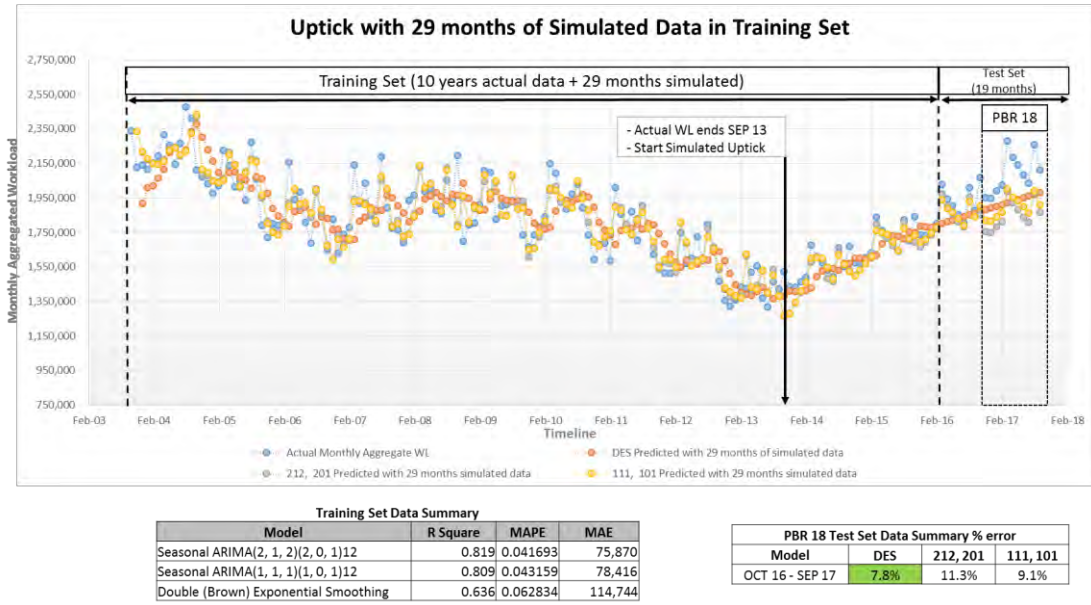
Figure 41.   Uptick scenario and forecasting results with 29 months simulation
data introduced

3.   Model Results Comparison

Based on results of the uptick and downtick sensitivity analysis, we select
ARIMA (1,1,1)x(1,0,1)12 as the final model. Although DES reacts faster to the uptick
simulation, ARIMA (1,1,1)x(1,0,1)12 has a more tapered reaction, which is less risky in
uncertain environments.

4.   Comparison with Current Regression

The next two sections compare results from our selected model, ARIMA
(1,1,1)x(1,0,1)12, with the current regression over two PBR cycles and translate the
workload results into the cost required to fulfill that workload.

a.   PBR 13 and 14 Comparison (% Error)

To see how well our selected model would have predicted workload if it were
used, we compared forecasts between our model, ARIMA (1,1,1)x(1,0,1)12, and the
current regression model DLA uses. We used PBR 13 and PBR 14 since we had actual
data to compare error against. We replaced actual values in DLA's current regression
model with DORRA numbers to keep our analysis consistent with the rest of our study.

The results, as shown in Figure 42, show that ARIMA (1,1,1)x(1,0,1)12 does a better job of predicting not only in the current year of execution, but also in the first and second years of the PBR cycle. For the first year of the PBR cycle (defined by FY12 in PBR 13 and FY13 in PBR 14), it improved the percent error by almost 42%. The current regression model had an average percent error of 8.01%, calculated by averaging 6.80% for FY12 in PBR 13 with 9.21% for FY13 in PBR 14. On the other hand, our ARIMA (1,1,1)x(1,0,1)12 model had an average percent error of 4.67%, calculated by averaging 1.13% for FY12 in PBR 13 with 8.203% for FY13 in PBR 14. For the second year (FY13 in PBR 13), it improved upon the current regression model by 47% from a 17.47% error with the current regression model to a 9.21% error with the ARIMA (1,1,1)x(1,0,1)12 model.

Fiscal Year	DORRA Actuals	PBR 13 Comparison				PBR 14 Comparison			
		DLA Regression	% Error	ARIMA (1,1,1)x(1,0,1)12	% Error	DLA Regression	% Error	ARIMA (1,1,1)x(1,0,1)12	% Error
FY 11	21,204,852	21,344,356	0.66%	21,226,394	0.10%				
FY 12	19,429,227	20,751,304	6.80%	19,648,517	1.13%	20,222,166	4.08%	19,744,574	1.62%
FY 13	17,013,701	19,985,451	17.47%	18,579,878	9.21%	18,580,313	9.21%	18,409,387	8.203%

Figure 42.   Comparison of ARIMA (1,1,1)x(1,0,1)12 to DLA's current regression model in PBR13 and PBR14 forecasts

b.   *Translation of Workload Forecasts into Cost Allocations*

To demonstrate the impact of workload forecasts on DLA Distribution, we convert the forecasted workload into a cost that DLA would allocate toward fulfilling the workload requirements. Using the current lines per paid equivalent (LP/PE) of 423 lines per month that DLA Distribution uses, we can estimate the average number of FTEs per month needed to fulfill the workload requirements. From this FTE number, we determine the average annual cost using a government civilian employee average cost of $43.07/hour (U.S. Department of Labor, Bureau of Labor Statistics, 2014) multiplied by the standard hours per year for government employees of 2,087 (Office of Personnel Management, n.d.). For the two years of the PBR 13 cycle, we calculate the cost for the actual workload experienced, the workload using the current regression model forecasted, and the workload our ARIMA (1,1,1)x(1,0,1)12 model forecasted. The result is illustrated

in Figure 43. If our ARIMA (1,1,1)x(1,0,1)12 model were used for PBR13, DLA Distribution could have theoretically saved 5.68% ($19.5 million) in the first year (FY12) and 8.26% ($24.9 million) in the second year (FY13).

PBR 13 Cost Comparison for Forecasted Values						
Fiscal Year	DORRA Actuals	DLA Regression	Regression Difference from Actual	ARIMA (1,1,1)x(1,0,1)12	ARIMA Difference from Actual	ARIMA's Difference from Regression
FY 12	$ 344,057,659	$ 367,469,337	$ (23,411,678)	$ 347,940,906	$ (3,883,247)	$ (19,528,431)
FY 13	$ 301,282,914	$ 353,907,420	$ (52,624,506)	$ 329,017,169	$ (27,734,255)	$ (24,890,251)
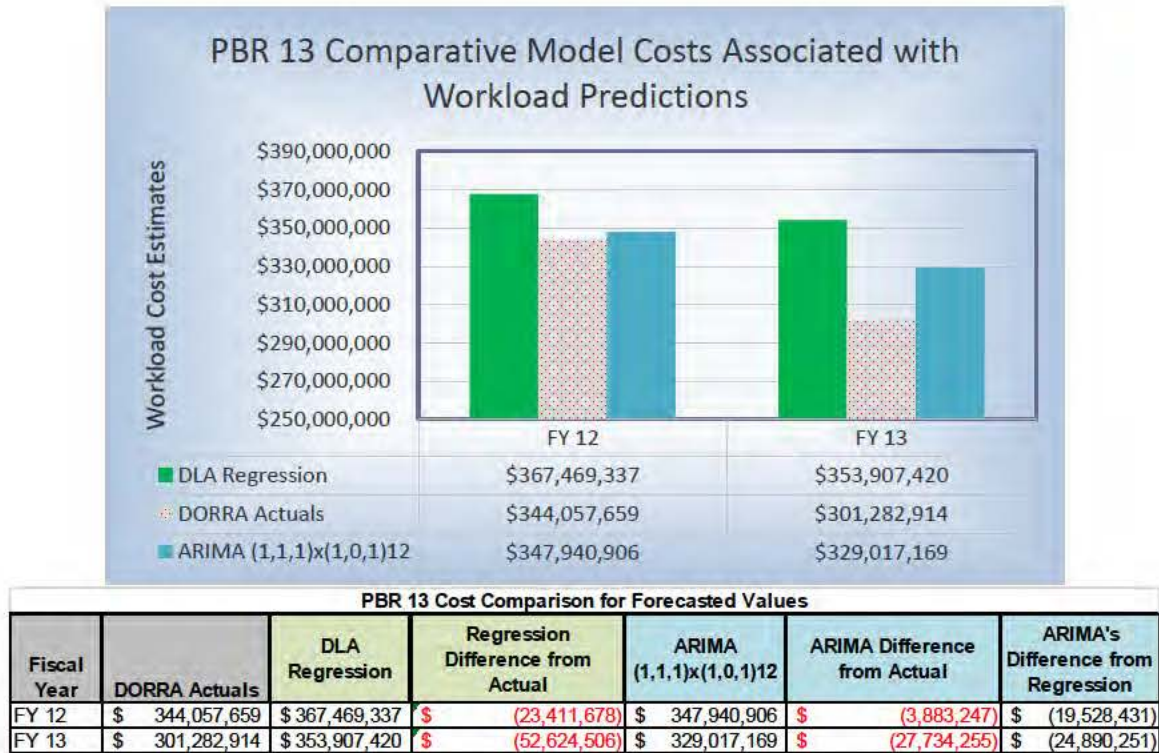
Figure 43. PBR13 cost comparison of current regression model forecast and ARIMA (1,1,1)x(1,0,1)12 forecast

We used the same process to predict for the current PBR cycle, PBR 16. Figure 44 displays the forecast results for the current year of execution, FY14, and the first two years of the PBR cycle, FY15 and FY16.

Fiscal Year	DLA PBR 16	ARIMA PBR 16
FY 14	16,051,329	15,173,472
FY 15	15,978,703	13,948,301
FY 16	15,919,855	12,737,427

Figure 44. PBR16 forecast comparison

For FY15, using ARIMA (1,1,1)x(1,0,1)12 would have led to 12.7% ($36 million) less in costs associated with the predicted workload then the current regression model. For FY16, these costs would have been 20% ($56 million) less (Figure 45).

Fiscal Year	DLA PBR 16	ARIMA PBR 16	Difference	FTE	Cost Difference per year
FY 14	16,051,329	15,173,472	73,154.76	172.94	$ 15,545,316.51
FY 15	15,978,703	13,948,301	169,200.14	400.00	$ 35,954,866.30
FY 16	15,919,855	12,737,427	265,202.35	626.96	$ 56,355,243.04

Figure 45.   PBR16 cost comparison of current regression model forecast and ARIMA (1,1,1)x(1,0,1)12 forecast

E.   SUMMARY

This chapter described how we analyzed the data series we gathered and our framework for forecast modeling and model comparison. We used "best-fit" determination to select models to analyze further for predictive characteristics. We then used a back-casting technique to further select the models that were best at prediction. Lastly, we selected our recommended model based on sensitivity analysis using an uptick and a downtick scenario. Our model was then compared to the current regression model to illustrate the monetary impact of how our model, if used, would have predicted workload over recent PBR cycles. The next and final chapter of this study provides our conclusions and recommendations to DLA as well as recommendations for further academic research related to this topic.

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V.   SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A.   SUMMARY

This project analyzed the current DLA regression model used to estimate DLA distribution processing workload. The distribution workload forecast is used to help properly staff distribution centers and set rates to fully recover costs. DLA's current forecasting method is not sufficiently predicting workload. We examined DLA's current method and developed multiple forecasting models in order to determine a more accurate method for DLA to predict workload.

In Chapter II, we discussed DLA's background and current regression model used to forecast its total workload. We identified factors and issues affecting the accuracy in predicting DLA Distribution workload and explained our understanding of the current model. We discussed previous studies on forecasting and described the forecasting methods we used in detail.

In Chapter III, we developed a methodology for our analysis and model formulation process to apply against the forecasting problem.

In Chapter IV, we examined the results for each model against their fit and accuracy in predicting future workload. We selected a final model, ARIMA $(1,1,1,)x(1,0,1)12$, determined to be the best-performing alternative to the current DLA method. Finally, we compared our workload model predictions against DLA's current process.

B.   CONCLUSIONS

Our research asked two primary questions. First, what are the shortcomings of the current regression model? Second, are better forecasting methods or tools available to provide more accurate forecasts?

The current linear regression model used by DLA to forecast distribution issues and receipts worked relatively well as business grew with expansion of military operations requiring services to buy more items, increasing sales and seemingly

increasing workload. As this cycle reversed, the model showed signs of weakness. The relationship between sales and workload may not be as significant where sales is the leading indicator causing workload. The relationship, symbolized by R^2, changes from year to year, indicating that there may be other external factors causing workload. Additionally, policy and supply chain accounts change, placing additional error into a forecast. Related to this is the fact that sales are also forecasted by the services and supply chains. Using forecasted sales, which have their own inherent error, to predict workload essentially compounds the error of the prediction.

We could not conclude that a regression model based on sales would be viable in the future. A separate study would be needed on how sales are forecasted and on the relationship between sales, workload, and other potential factors that may influence workload. This additional analysis was beyond the scope of this study.

In answering the second and principal question of our study, we conclude that time series models using as many years of data as possible are viable forecasting methodologies for predicting issues and receipts. ARIMA and DES performed well compared to the current regression. Specifically, an ARIMA (1,1,1)x(1,0,1)12 performed the best out of the models we tested using ten years of data. It was more responsive than an ARIMA (2,1,2)x(2,0,1)12 model during changes and forecasted better than a DES model, which was over-responsive to changes. It was able to predict workload for two recent PBR cycles (PBR 13 and 14) more accurately than DLA's current regression model. Our forecast error for the first and second years was 4.67% and 9.21%, respectively, equivalent to a 42% and 47% improvement over the current model's forecast error.

C.   RECOMMENDATIONS

Recommendations associated with this study are for DLA's operational use of this model and future forecasting execution as well as future academic research related with this topic.

1. Recommendations for DLA

There are several recommendations for DLA to incorporate that may enable a better distribution workload forecast. First, we recommend that DLA use ARIMA $(1,1,1)x(1,0,1)12$ based on its forecasting performance in this study. Second, reassessing the model periodically will help identify whether the current model is still the best model or whether a change is needed. Third, we recommend examining the use of multiple models in combination in a qualitative manner to achieve reliable forecasts. Periodic analytical assessment of the forecasting model is critical to maintaining accurate forecasts and relative flexibility to adjust. For example, the DES model reacted faster to drastic changes (as seen in the Uptick scenario), so an option may be to use both DES and ARIMA, along with managerial knowledge and judgment, to determine a more accurate forecast when a drastic change is occurring or is likely to occur.

If our recommended ARIMA model is incorporated, there are two additional ideas to consider. The first is an investment in a forecasting software tool, such as JMP, to facilitate running the model and analyzing the data and forecast results. A trained analyst using the software tool is needed to examine the outputs of the model and identify areas of present or future variability indicating a level of uncertainty or risk in the forecast. Second, we recommend running the model more frequently (perhaps quarterly) in order to track developing trends and the accuracy of the forecasting model. Perhaps the ARIMA model parameters need adjusting. Perhaps a model run at mid-year confirms adjustments that are planned.

Additionally, no forecast is 100% accurate. There is risk that is tied to each data point being predicted. The confidence intervals can give a statistical range of where the value is likely to fall. Understanding how the model behaves can give decision makers, based on their operational knowledge of past, current, and future activity, an idea of the level of this risk and what decisions regarding workload, staffing, and spending may be required.

2. Recommendations for Further Research

While conducting our research and analysis, we identified a number of areas that we felt warranted additional study. The first is a deeper look at workload cycles at DLA over time, or perhaps the PBR cycle itself, to determine if there is an ideal time period to best predict a full PBR cycle. In terms of this study, the question is what would be the best time period to use in the training set to predict workload in the PBR cycle of the test set.

Another recommendation for further study is to explore the use of a regressor with the ARIMA model. If sales is determined to be a causal indicator of workload, adding it as a regressor to the ARIMA model may enable the model to predict changes better adjusting with the signal that sales presents.

We also recommend further study on how sales are forecast. This may shed light on whether it is a useful mechanism for predicting issues and receipts and why it is or is not useful. As part of this or perhaps a separate study, an exploration of buying power over time and the effects that may have on the relationship between sales and workload would be a valid study.

Lastly, scaling the workload analysis down to a single distribution center and studying the process of how ground-level workload feeds into the staffing and spending systems may also be feasible. As an extension of this, examining how workload forecasts affect the pricing and staffing decisions for DLA Distribution as a whole would be a beneficial continuation of workload forecast analysis and its impacts.

These additional topics are areas beyond the scope of our study, but they would enhance the body of critical analyses of DLA systems, provide further insight and learning, and potentially identify efficiencies that DLA could implement for the future.

APPENDIX.　　　STUDY DATA

Month	FY04 Workload	FY05 Workload	FY06 Workload	FY07 Workload	FY08 Workload	FY09 Workload	FY10 Workload	FY11 Workload	FY12 Workload	FY13 Workload	FY14 Workload
OCT	2,336,766	2,111,822	1,791,196	1,646,744	1,775,431	2,194,918	1,735,017	1,736,002	1,621,013	1,470,272	1,183,390
NOV	2,127,511	2,071,595	1,719,436	1,824,888	1,763,890	1,697,467	1,665,695	1,594,489	1,552,906	1,355,308	1,187,549
DEC	2,142,586	2,031,420	1,801,680	1,630,390	1,691,682	1,794,915	1,733,820	1,681,813	1,514,477	1,321,014	1,116,096
JAN	2,116,250	1,977,207	1,788,615	1,737,870	1,936,765	1,805,924	1,781,444	1,687,057	1,513,444	1,358,237	1,203,572
FEB	2,152,158	2,018,551	1,807,705	1,777,768	1,965,260	1,909,861	1,840,752	1,584,494	1,527,046	1,430,723	1,203,774
MAR	2,193,576	2,223,887	2,155,602	2,140,739	2,126,517	2,106,678	2,148,006	2,008,023	1,751,014	1,425,667	1,394,603
APR	2,315,912	2,136,660	1,938,237	1,917,058	1,987,449	2,097,310	2,092,553	1,857,538	1,569,440	1,519,336	1,420,253
MAY	2,255,005	2,013,030	1,984,619	2,036,606	2,007,379	1,826,074	1,928,809	1,787,037	1,600,574	1,556,025	1,379,301
JUN	2,145,268	2,047,918	1,809,661	1,849,779	1,879,092	1,902,101	1,885,469	1,870,481	1,724,327	1,370,499	1,324,103
JUL	2,263,369	1,935,816	1,686,778	1,875,603	1,860,319	1,909,665	1,973,770	1,703,614	1,594,275	1,318,360	1,329,350
AUG	2,478,443	2,270,608	2,001,629	2,189,842	2,054,181	1,935,185	2,028,887	1,904,845	1,796,872	1,466,133	1,396,340
SEP	2,409,681	2,060,732	1,841,705	1,891,396	1,945,046	1,883,728	1,892,392	1,789,459	1,663,839	1,422,127	--
TOTAL	26,936,525	24,899,246	22,326,863	22,518,683	22,993,011	23,063,826	22,706,614	21,204,852	19,429,227	17,013,701	--

Table 5.　　Available data, in aggregated issues and receipts, used during this study and broken down by fiscal year.

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